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Impacts of COVID-19 on urban rail transit ridership using the Synthetic Control Method

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ABSTRACT

The outbreak of COVID-19 in 2020 has had drastic impacts on urban economies and activities, with transit systems around the world witnessing an unprecedented decline in ridership. This paper attempts to estimate the effect of COVID-19 on the daily ridership of urban rail transit (URT) using the Synthetic Control Method (SCM). Six variables are selected as the predictors, among which four variables unaffected by the pandemic are employed. A total of 22 cities from Asia, Europe, and the US with varying timelines of the pandemic outbreak are selected in this study. The effect of COVID-19 on the URT ridership in 11 cities in Asia is investigated using the difference between their observed ridership reduction and the potential ridership generated by the other 11 cities. Additionally, the effect of the system closure in Wuhan on ridership recovery is analyzed. A series of placebo tests are rolled out to confirm the significance of these analyses. Two traditional methods (causal impact analysis and straightforward analysis) are employed to illustrate the usefulness of the SCM. Most Chinese cities experienced about a 90% reduction in ridership with some variation among different cities. Seoul and Singapore experienced a minor decrease compared to Chinese cities. The results suggest that URT ridership reductions are associated with the severity and duration of restrictions and lockdowns. Full system closure can have severe impacts on the speed of ridership recovery following resumption of service, as demonstrated in the case of Wuhan with about 22% slower recovery. The results of this study can provide support for policymakers to monitor the URT ridership during the recovery period and understand the likely effects of system closure if considered in future emergency events.

1. Introduction

The ability to understand and accurately predict fluctuations in ridership of urban rail transit (URT) systems can help managers plan service adjustments effectively and in a timely manner. However, the outbreak of COVID-19 at the beginning of 2020, which caused an extreme decline in public transit ridership, especially in mass transit, has presented a significant challenge for transit planners. Restrictions, such as stay at home orders and city-lockdowns, change residents' daily activities. Besides, the public transit is vulnerable during the pandemic due to its collective nature of its mobility. Under such circumstances, determining the relationship between the ridership decline and the severity of the COVID-19 outbreak can provide transportation organizations with guidance on future ridership trends as many cities gradually recover.

Many researchers and organizations have investigated and reported on the negative impacts of COVID-19 on various aspects of public transportation. Most notably, many cities around the globe have experienced major reductions in public transit demand as a result of the substantially reduced economic activities. Work at home and online business became the new norm after the outbreak of COVID-19 (Zhang et al., 2021), contributing to reductions in passenger demand in the range of 80%–95% (Vickerman, 2021). Modal preferences by commuters were also impacted by the pandemic. For essential out-of-home activities, it was observed that commuters preferred the private car, cycling, and walking over public transit (Jenelius and Cebecauer, 2020; Zhang et al., 2021). However, modal shifts to cycling and walking were generally higher than the shift to the private car, as several cities introduced additional lanes for cyclists and pedestrians (EIT, 2020). On the supply-side, many transportation agencies have cut service levels to

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reduce costs and meet government restrictions on service hours (Wang and Noland, 2021). Such reductions have consequently contributed to further decline in public transit ridership. It is thus obvious that the COVID-19 pandemic has adversely affected public transit ridership, both directly and indirectly. On the one hand, fewer people were commuting to work and school, and those who commuted were less likely to use public transit due to the perceived health risks while travelling (Tan and Ma, 2020). On the other hand, the restrictions enforced by governments and transit agencies have limited the public transit service levels, contributing to further decline in transit ridership.

Public transit ridership is generally estimated using the four-step travel demand model or direct demand model (Miller et al., 2018). The latter type is an econometrics approach that estimates the direct relationship between ridership and its determinants. Many studies have used this type of model to study the influence of various factors on ridership (Campbell and Brakewood, 2017; Pereira et al., 2015; Yu et al., 2019). Unfortunately, the direct demand model is difficult to apply for analyzing ridership against the background of COVID-19. The spread of this disease has been extensive, influencing the entire urban society and economic activities. Hence, it is difficult to apply the traditional direct demand models due to their requirement of strict independence among variables. The Synthetic Control Method (SCM), which has exhibited excellent performance in policy studies, could address this challenge. The SCM provides a way for predicting the unobserved experiment status of a unit affected by an intervention (Abadie et al., 2010). It should be noted that the DID method has similar procedures with the SCM but requires a parallel trend between the treated and control units, which is challenging to meet in practice studies (Doudchenko and Imbens, 2016). The SCM can overcome the limitations of the DID method. In addition, SCM can be employed when the outcome is at the aggregate level (i.e., country or city). It can estimate the effect of the pandemic on URT ridership for a specific treated unit in the long term. Therefore, this paper employs the SCM to analyze the effects of COVID-19 on the URT ridership in various world cities, estimates the impact of the system closure in Wuhan during February 2020 on ridership recovery.

The presented study contributes to the literature on the relationship between COVID-19 and URT ridership in several ways. First, the quantitative estimation of the reduction in URT ridership caused by the pandemic could provide support for future responses from transit agencies. Compared with the pre-existing research, which focused on the mechanism of COVID-19's impact on urban mobility, this paper focuses on the effects of COVID-19 on URT ridership. Second, it further analyzes URT ridership reductions during the pandemic across several Asian cities, which can support transit planners' evaluations of the effects of different policies (e.g., the severity and duration of restrictions and lockdowns). Furthermore, the analysis of "system closure and reopening" can provide authorities with insights on ridership patterns during the recovery periods and inform policymaking regarding the system closure intervention in the event of a future wave of this pandemic. As the earliest city to report the confirmed cases, Wuhan can provide practical lessons, such as the long-term impact of COVID-19 on URT ridership. However, Wuhan's system closed entirely during February 2020. Thus, it is not very meaningful to estimate its ridership reduction (equaling zero in February). As another focus of the present study, the impact of system closure in Wuhan on ridership recovery is investigated.

The remainder of this paper is organized as follows. Section 2 presents a literature review of URT ridership analysis, the application of the SCM, and studies that examine the impact of COVID-19 on urban mobility. Section 3 describes the COVID-19 infection rates in different cities, provides details on the predictors and introduces the principles of the SCM. Section 4 presents the application of the SCM and discusses the effects of the pandemic on ridership in different cities and investigates the impact of the system closure in Wuhan on ridership recovery after the system re-opened. Section 5 provides conclusions for the study.

2. Literature review

2.1. Public transit ridership analysis

Typically, the determinants of public transit ridership are classified into four broad categories: built environment factors, service attributes, socio-economic characteristics, and others. The built environment factors show strong significance in transit usage analysis (Miller et al., 2018). The service attributes are commonly identified as the primary factors when forecasting public transit ridership (Diab et al., 2020). Social and economic characteristics usually reflect the economic development status of specific cities. Other factors, such as weather, influence both the choice of passengers to travel and the operation of the system (Zhou et al., 2017). Furthermore, the type of technology applied in public transit systems can influence ridership (Brakewood et al., 2015).

In contrast to the ridership analysis at the system-wide level, both the station and line levels have received attention in various studies. At such levels, other methods of panel regression techniques with demonstrated high performance have been used, including the cross-sectional model, time-series model, and the combination of the two (Brakewood et al., 2015). Moreover, the application of the autoregressive integrated moving average method, and geographically weighted regression model provide excellent performance, especially for time series and geographical analyses (He et al., 2020). Data mining methods, such as support vector machine have been used by some researchers, prompted by the abundant availability of data related to ridership (Wang et al., 2018).

A policy's effect on ridership is generally estimated via comparative case studies, as seen in studies on the effects of bike-sharing, slow zones, and gentrification of station areas (Bernal et al., 2016; Campbell and Brakewood, 2017; Chakour and Eluru, 2016). However, an opportunity exists to apply other methods based on the precondition that the dummy variable representing the policy in question is independent of other variables in the model. An alternative method of analyzing the effects of new technology on ridership is using the difference in differences (DID) model. Campbell and Brakewood (2017) described a representative example of using the DID model in ridership analysis. In the inference section of the book written by Cameron and Trivedi (2005), the SCM is described as a variant (i.e. particular case, transform) of panel regression methods using the DID concept under a more relaxed constraint. Therefore, it is possible to use the SCM to estimate the COVID-19 effect on URT ridership. Combining the ideas of other researchers (Guzman et al., 2019), the efficacy of applying this method can be confirmed.

2.2. Application of SCM

SCM is widely used in comparative case studies because of its flexibility with the selection of the comparison unit and the ability to overcome uncertainty, which is not well represented by the standard errors when using traditional inferential techniques (Abadie et al., 2010). Abadie and Gardeazabal (Abadie and Gardeazabal, 2003) used the SCM initially in 2003, in which two Spanish regions were selected to approximate the economic growth in the Basque region without terrorism, indicating the extent of the negative effect of terrorism on the economy. Based on this central idea, the researchers then analyzed tobacco consumption in California and the effect of Proposition 99 (Abadie et al., 2010).

The SCM has also been used extensively for policy analysis, especially economic-related analysis. The effect of the 1990 German reunification on West Germany was estimated, indicating a negative relationship between reunification and GDP per capita (Abadie et al., 2015). Hsiao et al. (2012) analyzed the impact of the political and economic integration of Hong Kong with mainland China based on the panel data of 24 countries. With the improvement of the SCM theory, its application extended to research areas beyond economics. An innovative application of the SCM, featuring multiple treated units instead of a single unit, was proposed for health policy estimation (Experiments, 2008). The reduction effect of gun laws on suicide was identified in Massachusetts (Kahane and Sannicandro, 2019). Furthermore, the application of the SCM to estimate effects was used in transportation analysis. One of the latest representative studies was an analysis of the fare elasticities on ridership for Bogotá's BRT system (Guzman et al., 2019). Another study focused on the air travel ridership changes against a background of aviation tax effects (Borbely, 2019). In both studies, the SCM was an appropriate method to produce counterfactual experiments.

2.3. Examination of the impact of COVID-19 on urban mobility

Several efforts have been made to assess the impacts of COVID-19 on traffic injuries and congestion (Lee et al., 2020; Oguzoglu, 2020). Other studies have analyzed quantitatively the effects of COVID-19 on urban mobility. For example, to evaluate the changes in modal distribution and journey purpose of commuters after the pandemic, Aloi et al. (2020) compared urban mobility levels before and during the confinement by re-estimating the origin-destination trip matrices, finding that public transport ridership in Santander (Spain) has dropped by about 93%. Arimura et al. (2020) reported travel demand reduction in Sapporo (Japan) due to the declaration of emergency after COVID-19. Fewer studies have investigated the impact of COVID-19 on metro ridership. Chang et al. (2021) examined metro usage at the station-level in Taipei during the pandemic using a DID model, indicating the correlations between confirmed cases and ridership reduction. The decline in subway ridership in New York City was examined by controlling for weather patterns using Ordinary Least Square (OLS) models based on time-series data, indicating modal shifts from subway to bike share system (Teixeira and Lopes, 2020; Wang and Noland, 2021). Liu et al. (2020) examined the impacts of COVID-19 on public transit demand in many public transit systems in the United States using a logistic growth function, indicating that the communities with higher proportions of essential workers tend to maintain higher levels of demand during COVID-19. Hu and Chen (2021) investigated the ridership reduction caused by COVID-19 using a Bayesian structural time series model, which examined the relationship between ridership decline and various internal and external factors comprehensively. Another representative study was conducted for several Chinese cities, examining subway's daily ridership using a SCM model. The study analyzed the effects of the fare-free public transport policies during the ridership recovery period (Dai et al., 2021). That study provides insights and support for our study.

3. Data and analytical method

3.1. Samples and COVID-19 infection rates

Studying cities in both China (the earliest country to witness the pandemic) and the US (a later one with high infection rates) could provide deep insights into the pandemic's effects on ridership. Selected cities in other countries are also included to ensure the wide applicability of this study. It should be noted that many residents of the treated cities relocated into neighboring cities and other megacities in China after the pandemic (Lai et al., 2020). Thus, there exists regional interrelationships and possible spatial-spillover effect of COVID-19 (Ehlert, 2021). Seven Chinese mainland cities situated around Wuhan (the first city that reported confirmed COVID-19 cases) at different directions and distances are chosen to account for the regional interrelationships and possible spatial-spillover effect of the impact of COVID-19 (shown in Fig. 1). The 11 control cities covering the major hubs in the UK, Spain, and the US, have well-established URT systems operating heavy rail and/or light rail, which are similar to the Asian cities. Other cities with identical URT characteristics, such as Tokyo, are dropped because of their unavailable detailed published ridership data.

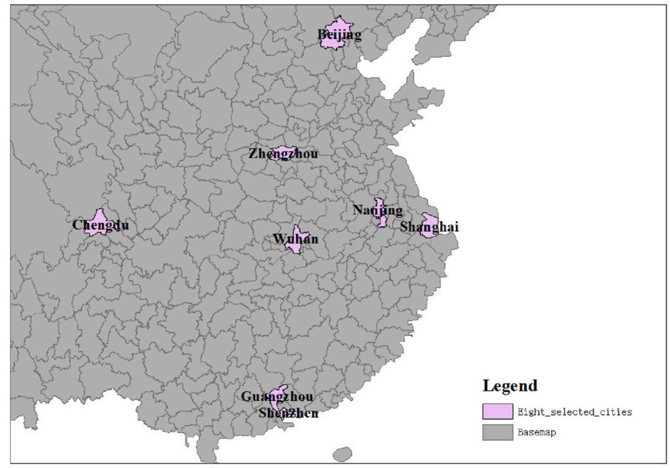

Fig. 1. A map of the seven Chinese cities that situating around Wuhan.

For an improved understanding of the pandemic spread in each city, the infection rate (i.e., confirmed cases divided by population) is selected to reflect the infection status. The infection rate of the cities considered in this research from December 2019 to September 2020 are depicted in Fig. 2.

Fig. 2 illustrates approximately two peaks during the nine-month period. The first peak primarily represents the cities in mainland China, and the second peak represents the cases in cities in the US and other countries. There is a one-month gap between the two peaks, which is consistent with the timeline reported by World Health Organization (2020). Wuhan had the largest infection rate compared to other cities before March. The rapid spiking of the infection rates in the selected cities represent outbreaks at different times. The cases in the US cities increased to a remarkable level since March 2020. It is noticeable that the infection rate in Miami went up sharply in July 2020 due to the backlog of test results (Florida Health Care Association, 2020). Excluding Miami, the infection rate in New York City and Boston were generally the highest during the nine-month period.

The daily ridership calculated using unlinked trips is used to inspect the steep decrease in URT. Notably, the URT in this paper includes both heavy rail and light rail, excluding streetcars. The reduction in URT ridership for each city is depicted in Fig. 3 and Fig. 4.

Daily ridership in specific metropolitan cities in China is excessively large compared to other cities in the study, as shown in Figs. 3 and 4. To distinguish the daily ridership trends in the cities with smaller ridership from that in New York City, Fig. 4 employs a logarithm y-axis. After January and March 2020, when the pandemic outbreak in China and the US respectively, there are two apparent reductions in daily ridership in the 22 cities. The reduction in most Chinese cities (as shown in Fig. 3) is larger than that in most US cities (as shown in Fig. 4). In Figs. 3 and 4, in the previous year, there is no obvious change in each city, except for the slight decline for February and August 2019, which overlaps with the spring festival in China and the summer vacation in Spain. Fig. 3 shows that ridership in most Chinese cities exhibited a recovery pattern as the infection rate plateaued after March 2020. Fig. 4 shows ridership in New York in January 2020 increased dramatically which is attributed to improved on-time performance (MTA, 2020). Cities outside Asia experienced a similar trend after May 2020 with a slighter recovery, which indicates that although the infection rate keeps rising, relaxing several restrictions during the city's reopening stage contributed to the recovery.

3.2. Data collection and assembly

This study uses monthly city-level panel data for the period of January 2019 to June 2020. Since the COVID-19 outbreak started in

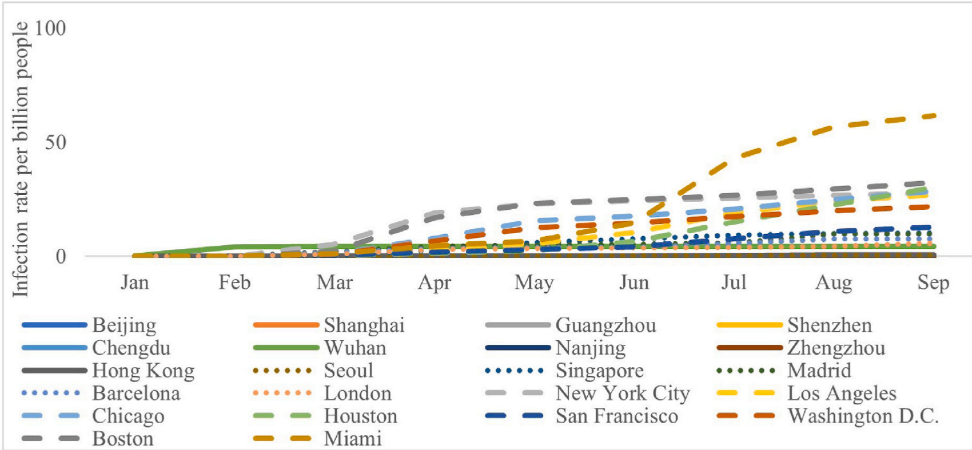

Fig. 2. Infection rate of COVID-19 from January to September 2020.
*Data collection sources: (Abbott et al., 2020; Dong et al., 2020; Ministry of Health of Singapore, 2020)

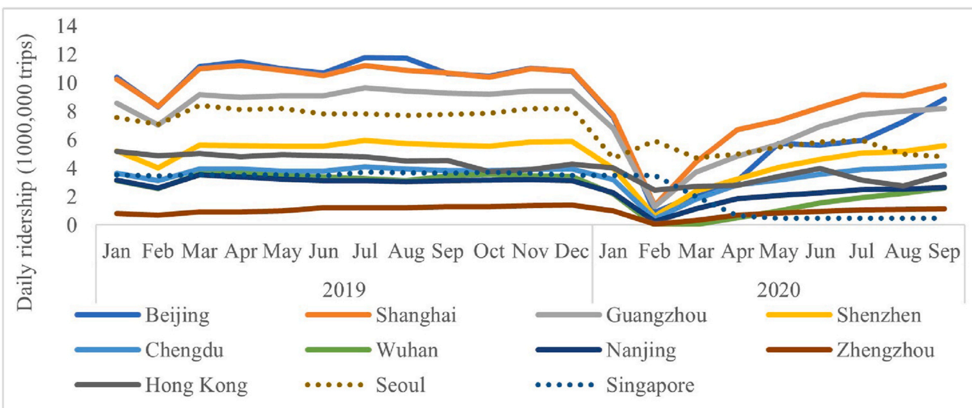

Fig. 3. Daily ridership trends in Asian cities from January 2019 to September 2020.
* Data collection sources: (Department of Statistics Singapore, n.d.; Mass Transit Railway, 2020; Ministry of Transport of the People's Republic of China, 2020; Seoul Mero, 2020)

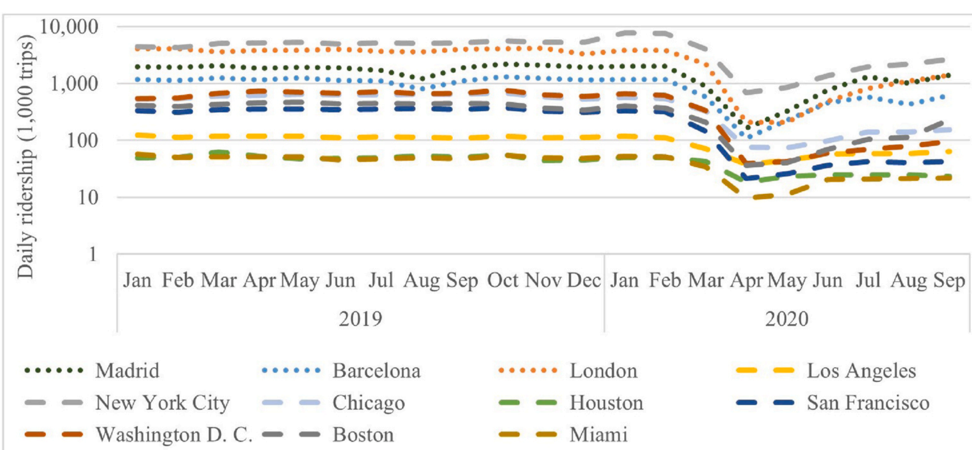

Fig. 4. Daily ridership trends in cities outside Asia from January 2019 to September 2020.
* Data collection sources: (American Public Transportation Association, 2020; Government of UK, 2020; National Institute of Statistics of Spain, 2020)

January 2020 according to WHO's announcement (WHO, 2020), we extended the research period back to the same month in 2019. The data after June 2020 are not considered since several cities in the US implemented economic recovery measures. The data frame consists of six variables as predictors: population, GDP per capita, fare, number of stations in the URT network, the system's age (the difference between the opening year and the current year), and the average operating speed of the train across the network. Table 1 presents the sources and

Table 1
Sources and summary statistics for predictors.

Units			Source		
Cities in the U.S.			APTA		
Madrid, Barcelona			Centro Nacional de Epidemiología		
Seoul			Open Data Plaza of Seoul		
Singapore			Singapore's Public data		
Hong Kong			Transport Department of Hong Kong		
Cities in Mainland China			China Association of Metros		
London			Office of National Statistics, U.K.		
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
URT Fare (USD)	420	1.08	0.73	0.28	2.75
System's Age	420	55	45	6	156
Average Speed (km/h)	420	30.78	6.96	14.47	48.47
Number of stations	420	219	121	23	472
Population (1000 people)	420	9316	6244	706	24,200
GDP per capita (USD)	420	49,686	25,717	14,753	100,225

*Obs. = 8*21 + 14*18. The samples in the eight Chinese mainland cities were collected for January 2019–September 2020 (21 months), the samples in other cities were collected for January 2019–June 2020 (18 months).

statistics of variables for selected cities.

One variable is used as the dependent variable: the relative change in daily ridership, which is defined as follows:

$$relative\ change\ in\ daily\ ridership = \left(daily\ ridership_{m_i} - daily\ ridership_{m_i,\ 2018}\right) \Big/ \ daily\ ridership_{m_i,\ 2018} \tag{1-1}$$

$$relative\ change\ in\ daily\ ridership^{*} = \left(daily\ ridership_{m_i} - average\ daily\ ridership_{2018}\right) \Big/ \ average\ daily\ ridership_{2018} \tag{1–2}$$

where m_i indicates the sequence of months (e.g. $m_i = 1$ for January 2019, $m_i = 17$ for May 2020), $dailyridership_{m_i}$ is the average daily ridership for m_i, $dailyridership_{m_i,2018}$ is the average daily ridership for m_i in 2018, $averagedailyridership_{2018}$ is the mean of the average daily ridership across the 12 months in 2018.

The rationale for variable selection is as follows. First, the predictors controlled in this paper represent the three broad categories generally used in ridership forecasting: built environment factors, service attributes, and socio-economic characteristics. Therefore, the controlled predictors can adequately explain the relative change in daily ridership. The population density and GDP can reflect both built environment and socio-economic attributes of each city, while the number of stations and the age of a URT system can be used to reflect the built environment status of that system and to a lesser extent its service attributes (system coverage). The fares and the operation speed of the URT system can be used as indicators of the service level of each URT system. Other service-related attributes, such as frequency, were dropped because they were affected by the pandemic, making them difficult to employ in the model. Second, the definitions of the relative change in daily ridership are derived from previous studies. It is challenging to employ the SCM if the outcomes in the selected cities are not comparable (e.g., the ridership of some Chinese cities is higher than in US cities). One potential solution to this issue is to transform the outcome to time differences, growth rates, or differences with respect to pre-intervention means (Abadie, 2021; Ferman and Pinto, 2019). Thus, this paper uses the relative change in daily ridership as the dependent variable. The effect of China's spring festival in February 2019 and the summer vacation in Madrid and Barcelona in August 2019 can lead to the monthly variation differing among countries. Thus, this paper employs the relative change in daily ridership concerning the time differences at the same month between the current year and 2018 (relative change in daily ridership) in Section 4.1, removing the influence of monthly variation in August and February. Besides, the relative change in daily ridership concerning pre-intervention means (relative change in daily ridership*) can reflect the effect of China's spring festival in February 2019, allowing for the ridership recoveries after the spring festival and system closure to be compared. Thus, this paper employs relative change in daily ridership* in Section 4.2 to investigate the long-term effect of COVID-19 on Wuhan's URT ridership recovery. The daily ridership data, the number of stations, average train speed, and system's age are collected from the transit authority website for each URT system. Notably, the daily ridership data in the 22 covered cities are unlinked ridership, which encompassed transfer trips according to the agencies that published the ridership data. The population and GDP per capita are collected from the Statistics Bureau of each city. Only the data in the period before the pandemic for population and GDP is applied in synthetic control.

Several key points should be discussed concerning the data. First, fare rates and structures in different cities vary, which presents a challenge in this comparative study. For consistency, the fare is collected from a report published by the Union Bank of Switzerland (UBS, 2015). For the cities considered in our study but not included in the report, the fare is recorded according to neighboring cities available in the report and has a comparable fare level at present. Second, URT fare is assumed to remain stable during the pandemic because of few changes on a year-on-year basis from 2019 to 2020. The number of stations remained stable except for the month when new stations or lines were opened. Since the four variables (population, GDP per capita, the average operating speed of trains, and system's age) are available at one-year intervals (i.e., 2019 and 2020), the data every two months are calculated by linear interpolation. Linear interpolation is a conventional approach to producing estimates for missing data, assuming natural linear propagation of estimates between two consecutive intervals (Huang, 2021). This approach is conducted using the "ipolate" command in STATA 15.0. All parameters are applied using a logarithm form to eliminate different parameters' measurement effects.

3.3. Analytical method - the SCM

The principle of the SCM is introduced based on the notation proposed by Abadie et al. (2010). Suppose there are + 1 regions observed for T periods and only the first region (treated unit) is exposed to an intervention (e.g., COVID-19 outbreak in this case). Suppose T_0 is the time at which the intervention was applied. The observed outcome Y_{jt} in region j at time t can be written in two parts, the potential outcome due to predictors (Y_{jt}^{N}) and the estimated effects (α_{jt}) of the intervention, as:

$$Y_{jt} = Y_{jt}^{N} + \alpha_{jt}D_{jt} \tag{2}$$

$$Y_{jt}^{N} = \delta_t + \lambda_t\mu_j + \theta_t Z_j + \varepsilon_{jt} \tag{3}$$

where δ_t is a constant factor across all units, Z_j is a vector composed of the predictors not affected by the intervention, μ_j is a vector of unobserved predictors, and θ_t,λ_t are two vectors of coefficients. D_{jt} is a dummy variable with value 1 if unit j is exposed to the intervention and 0 otherwise. ε_{jt} is an error term.

Both D_{jt} and Y_{jt}^{N} are required to estimateY_{jt}. However, $Y_{jt,t\le T_0}$ can be observed, which equals $Y_{jt,t\le T_0}^{N}$ because α_{jt} equals 0. For $t > T_0$, for the threated unit, Y_{1t}^{N} is not observed. Estimating the effect of the intervention with SCM requires creating a "synthetic control unit", which is a weighted combination of other units which are not exposed to the intervention. Consider a vector $W = (w_2, \cdots, w_{J+1})$ where w_j is a weight for each potential unit that contributes to the weighted combination when creating the "synthetic control unit"; then,

$$\widehat{Y_{1t}^N} = \sum_{j=2,\cdots,J+1} w_j Y_{jt} \tag{4}$$

The weights can be combined with the predictors as follows:

$$\sum_{j=2}^{J+1} w_j Z_j = Z_1 \tag{5}$$

The estimation process for vector W is proposed in the literature (Abadie et al., 2010), as well as the significance of the estimation. The estimation of $W$is achieved by Stata 15.0 using the "synth" command in this study. The outputs of this command include W, variables' balance, and the root mean square prediction error (RMSPE). W includes the optimal combination of weights, which are obtained by minimizing the discrepancy between the vector of pre-intervention characteristics for the treatment unit and that for the control units. The RMSPE is the average of the root squared discrepancies between Y_{1t}in the treated unit and its synthetic counterpart $\widehat{Y_{1t}^N}$ during T periods and is written as follows:

$$RMSPE = \sqrt{\sum_{t=1}^{T} \left(Y_{1t} - \widehat{Y_{1t}^N}\right)^2 \Big/ T} \tag{6}$$

RMSPE before T_0 can measure the quality of the estimation of $\widehat{Y_{1t}^N}$ where a near-zero RMSPE indicates better qualification.Abadie and Gardeazabal (2003)also introduced a placebo test method to assess the significance of the SCM. In the placebo test, one of the control units is assigned as the pseudo treatment unit, while the remaining untreated cities are assigned as potential control units for the pseudo. For example, set the unit $j = 2$ as the treated unit and the rest as the control units that can generate $\widehat{Y_{2t}^N}$, the effect estimated by the placebo test (i.e. α_{2t}) is the gap between $\widehat{Y_{2t}^N}$ and Y_{2t}. The placebo test executes multiple times for cities in the control group, and a series of estimated effects ($\alpha_{jt}, j = 2, \cdots, J+1$) can be obtained. Then the placebo test results can assess whether the effect estimated by the intervention for the treated unit (α_{1t}) is relatively large compared with that of the random assignment results for cities in the control group ($\alpha_{jt}, j = 2, \cdots, J+1$). The intervention's significant effect can be confirmed if α_{1t} is the largest effect among all estimated effects.

4. Estimation and discussion

4.1. COVID-19 impacts on URT ridership in asian cities

Before implementing the SCM, its basic settings (intervention, the treatment period and the treated unit) should be discussed and confirmed. In the case of COVID-19, the intervention setting is more challenging due to the complex relationship between the pandemic and URT ridership. Although previous research generally set the restrictions and lockdowns as the intervention (Dai et al., 2021), it is not appropriate to disregard the companion effect of health risks perceived by citizens on ridership reduction. According to previous studies, the outbreak of COVID-19 is a common cause of lockdowns and perceived health risks (Loske, 2020; Zhang, 2021). This means that without restrictions and lockdowns, the ridership can decrease due to the health risks perceived by citizens. Therefore, the COVID-19 outbreak, instead of lockdowns, should be set as the intervention in this study. It should be noted that only the ridership reductions in January and February 2020 are considered when assessing the effect of COVID-19 on URT ridership. The outbreak of COVID-19 and lockdown times in Europe and the US, which occurred after February, should not influence the results.

However, it is difficult to specify the exact time of the intervention. Because the virus first appeared in any given city due to the possibility of initial asymptomatic cases. Therefore, the outbreak time is selected according to WHO's announcement. The news release by the WHO declared the infections of COVID-19 in China in January of 2020 and then proclaimed that COVID-19 was a pandemic in March after the sharp increase of cases globally (WHO, 2020). Therefore, the treatment period is either January or March. It is possible to form a control group (which is required to be unexposed to COVID-19) if the intervention time is set before the outbreak in the US; therefore, the treatment period for Asian cities is set to January 2020. The 11 cities in the sample—Beijing, Shanghai, Guangzhou, Shenzhen, Chengdu, Wuhan, Nanjing, Zhengzhou, Hong Kong, Seoul, and Singapore—are used individually as treated units; the remaining cities in the US and Europe in which an outbreak occurred later than the former group are used to construct the synthetic control unit. Figs. 5 and 6 display the SCM and placebo test results for the 11 cities in the treated group and Table 2 presents the numerical outputs for the same cities.

Fig. 5 illustrates the comparison between the relative change in daily ridership of the treated city and that of the synthetic control unit. The solid treated unit curve is the observed relative change in daily ridership (i.e., Y_{1t}). The dotted synthetic control unit curve is the fitted relative change in daily ridership (i.e., $\widehat{Y_{1t}^N}$), indicating the likely pattern of the relative change after January 2020 in the absence of the pandemic's influence. The gap in Fig. 6 is the estimated effects of COVID-19 (i.e., α_{1t}, the difference between Y_{1t} and $\widehat{Y_{1t}^N}$). The black curves in Fig. 6 represent the estimated effects for the pandemic's treated unit in January 2020, and the brown curves (placebo tests) are the estimated effects for cities in the control group.

As shown in Fig. 5, the synthetic control unit curves in seven cities (Beijing, Shanghai, Guangzhou, Shenzhen, Nanjing, Seoul, Singapore) are at comparable levels with the treated unit curves before January 2020, which means the synthetic control units can reasonably interpret the relative change in daily ridership reasonably well for these treated units. The selected western cities were sufficient and appropriate to approximate the counterfactual ridership changes for the treated units due to the near perfect fit of the synthetic control curves in the seven cities. However, there are discrepancies with an apparent gap between the two kinds of curves in the other four cities (Chengdu, Wuhan, Zhengzhou, and Hong Kong). The rapidly extend URT network topology in Chengdu, Wuhan, and Zhengzhou can be responsible for that. Chengdu and Zhengzhou opened 68 and 79 stations in 2019–2020, while Wuhan extended a trunk subway line across the downtown area transferred with a split suburb line (Metros, 2019). The ridership decline is related with a series of demonstrations during the fourth quarter of, 2019 in Hong Kong. After January 2020, the corresponding synthetic control unit curves increased slightly in February 2020 when the pandemic was not in effect for potential control cities. In contrast, the treated unit curves declined when the pandemic affected the treated cities, except in Singapore. The lower confirmed cases (less than 100) and delayed restrictions (after March 2020) in Singapore can be potentially responsible for that. Although the synthetic control unit curves start decreasing in March 2020 (when the pandemic outbreak occurred in the U.S.), the comparison between the treated and the synthetic control units in January and February 2020 could illustrate the effects of the pandemic by comparing the two different trends in the treated and the synthetic control units. The increase in the treated unit curves after March 2020 is due to the recovery and reopening of the 11 treated cities.

As shown in Fig. 6, the curves of seven treated cities (Beijing, Shanghai, Guangzhou, Shenzhen, Nanjing, Seoul, and Singapore) are around zero before the outbreak of the pandemic in January 2020, indicating that the gap between the treated unit curve and the synthetic unit curve is small for both treated and placebo cities. This means that

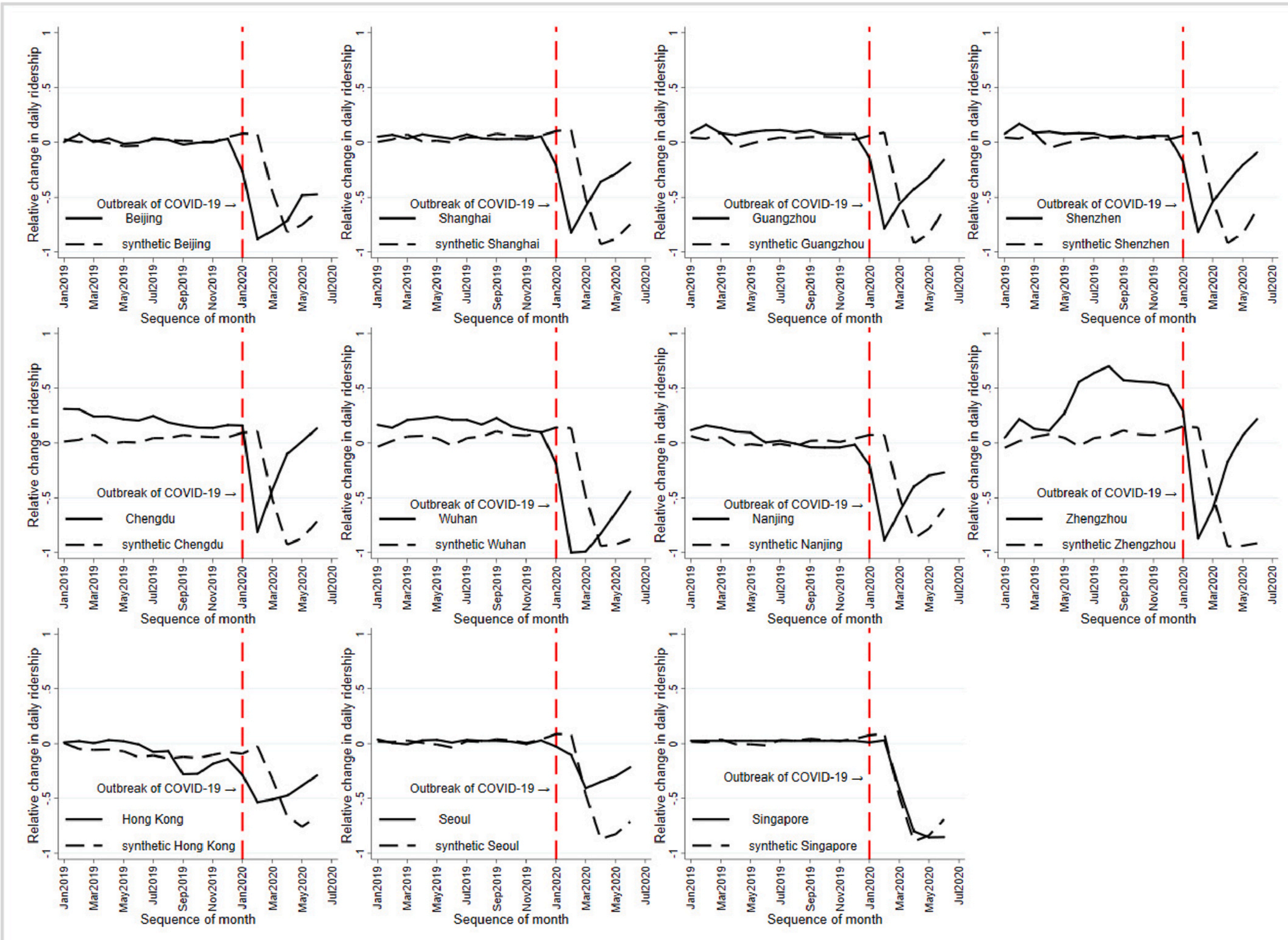

Fig. 5. SCM results for 11 cities.

the synthetic control units can perfectly fit the pre-intervention outcome of their treated units. After January 2020, the gap for the treated cities (in black) is visibly large compared to that of the placebo cities (in brown), reflecting the negative effect of COVID-19 on ridership reduction. In terms of the four excluded cities, which show imperfect synthetic results (as shown in Fig. 5), the gap between the two kinds of curves before the pandemic outbreak in January 2020 is larger than zero. Thus, the synthetic control unit can not capture the trajectory of the pre-intervention outcome in the treated unit. Under such circumstances, the effect of COVID-19 on URT ridership can not be estimated by SCM, although the gap is enormous in the post-intervention period (after January 2020).

To evaluate the gaps for treated cities that are relatively larger than the rest, this paper uses the method employed by Abadie et al. (2010). The distribution of the ratio of RMSPE before and after COVID-19 is calculated as follows.

The numerator is the RMSPE after the outbreak of COVID-19. Considering that the pandemic outbreak in the U.S. occurred after February, the gap after February 2020 is a combined reaction for both the reduction in the treated and control units. Therefore, the effects of COVID-19 on ridership are only explained by the gap in January and February 2020. The denominator is the RMSPE before January 2020. Fig. 7 gives the frequency distributions for the 11 cities.

Each sub-figure in Fig. 7 displays the distribution of the ratio of RMSPE before and after COVID-19 for one treated city and 11 control cities. Therefore, there are 12 RMSPE ratios in each sub-figure, with the one for the treated city clearly labelled. Except for Chengdu, Wuhan, and Zhengzhou, all ratios for the other treated cities stand out on the right of each distribution with considerably larger values than those for the control cities in the same graph. Therefore, the estimated effect of COVID-19 is meaningful. The ridership in Chengdu, Wuhan, and Zhengzhou was already fluctuating before the pandemic outbreak,

$$\text{ratio of RMSPE} = \sqrt{\sum_{t=Jan2020}^{t=Feb2020}\left(Y_{1,t}-\widehat{Y}_{1,t}^{N}\right)^{2} \Big/ (Feb2020-Jan2020+1)} \Bigg/ \sqrt{\sum_{t=Jan2019}^{Dec2019}\left(Y_{1t}-\widehat{Y}_{1t}^{N}\right)^{2} \Big/ (Dec2019-Jan2019+1)} \tag{7}$$

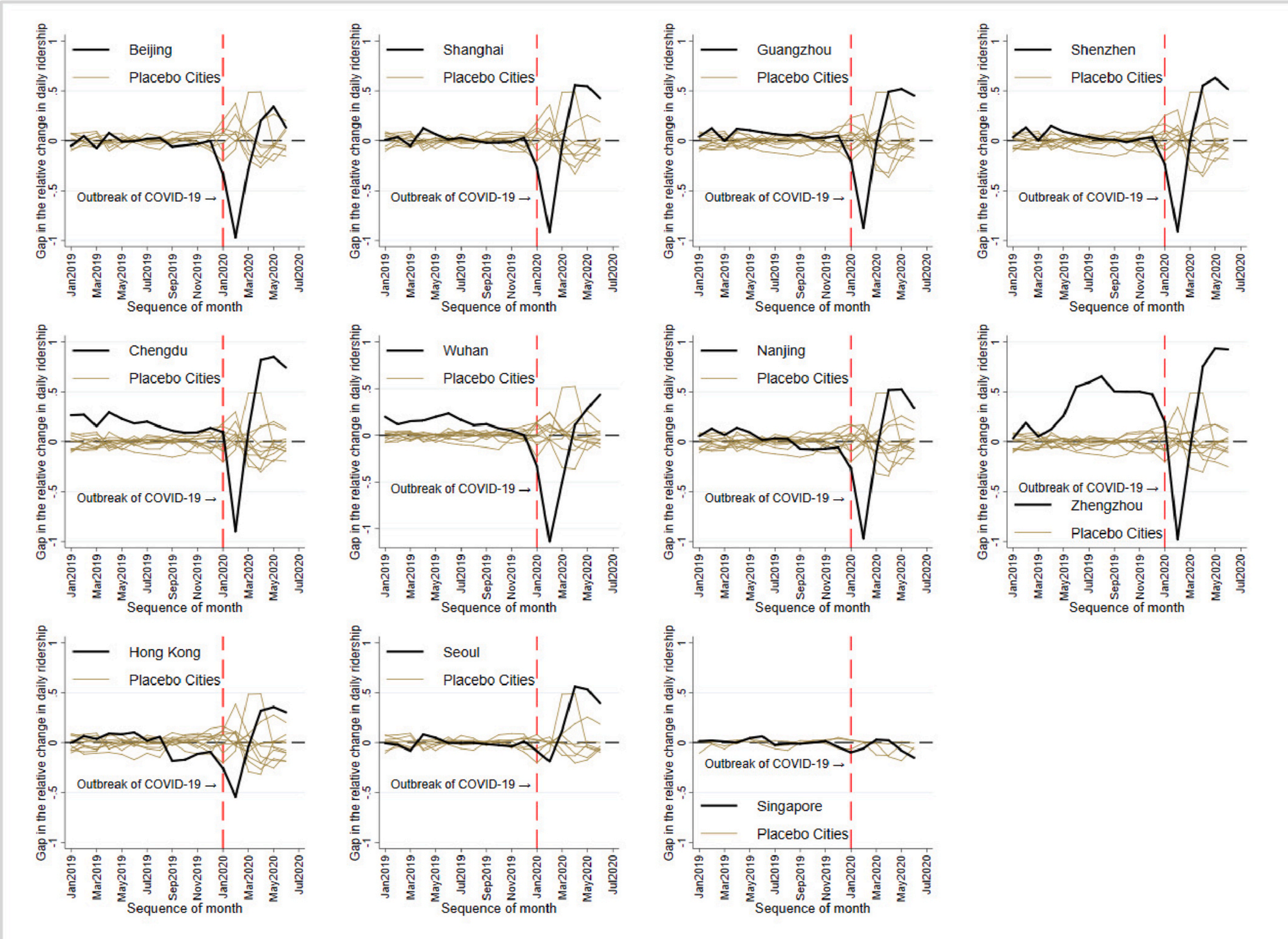

Fig. 6. Placebo test results for 11 cities.

responsible for the relatively small ratio. Although the ratio in Hong Kong is relatively larger than in the placebo cities, it can not illustrate the effect of COVID-19 on ridership since the outcome already decreased before the pandemic outbreak because of the demonstrations.

Table 2 provides the outputs of the SCM. The RMSPE (calculated from January to December 2019) varies within 0.03–0.09 for the treated cities except three (Chengdu, Wuhan, and Zhengzhou), which indicates that the synthetic control unit's relative change in daily ridership before the pandemic is close to that of the treated unit. The three excluded cities have larger RMSPE; thus, the pre-intervention synthetic control outcomes were biased and cannot represent the counterfactual outcome of the three cities. That conclusion corresponds to the placebo test results (as shown in Fig. 7). The estimated effect of COVID-19 in February 2020 is approximately 0.9 for most Chinese cities, which represents a ridership relative reduction of about 90%, whereas it was smaller for Hong Kong, Seoul, and Singapore (51%, 19%, and 6% respectively), indicating a higher reduction in the relative change in daily ridership in most Chinese cities than in Hong Kong, Seoul, and Singapore. These results warrant further attention. First, the outbreak of COVID-19 in the treated cities was clustered in January 2020, which means that the different outbreak dates of COVID-19 in the treated cities have little impact on the unequal ridership reductions. Second, the unequal ridership reductions are less likely the result of the disparate infection rate among cities. The estimated reduction in the former eight Chinese cities, which does not correspond with their infection rates, can provide evidence for that. For example, the infection rate in Beijing is lower than that in Guangzhou, whereas the estimated reduction is larger. Under such circumstances, the health risks perceived by citizens and the restrictions and lockdowns are potentially responsible for the unequal reductions among the treated cities. According to the perceptions-related research, the health risks perceived by citizens are similar (Attema et al., 2021; Mondino et al., 2020). Thus, it is reasonable to infer that the unequal reductions are associated with the restrictions and lockdowns among different treated cities.

Two potential inferences explain the association. First, earlier reactions to the pandemic can result in a more considerable ridership reduction. Chinese mainland cities imposing lockdown earliest at the end of January experienced a more considerable ridership reduction than other cities. Besides, the overall reduction of ridership in Hong Kong, Seoul, and Singapore (−51%, −19%, and −6%, respectively) has corresponded with their lockdown times (Fig. 8). Second, the severity of the restrictions can influence the extent of reduction of URT ridership. According to previous research, Chinese mainland cities adopted much more severe restrictions during the pandemic than Seoul, Hong Kong, or Singapore (Meep, 2020). Instead of strict stay-at-home orders, these three cities adopted less restrictive responses combined with transparency, comprehensive testing, and quick quarantining and isolation. Thus, it can be inferred that the severity and duration of restrictions and lockdowns can influence the extent of URT ridership reduction. Understandably, on the one hand, in governments that provided earlier reactions, cities may experience longer lockdown duration and thus have a more considerable ridership reduction. On the other hand, government regulations can induce citizens' perception of health risks during the pandemic, leading commuters to become afraid about

Table 2
Outputs for 11 treated cities.

SCM		No.1	No.2	No.3	No.4	No.5	No.6	No.7	No.8	No.9	No.10	No.11
Treated unit		Beijing	Shanghai	Guangzhou	Shenzhen	Chengdu	Wuhan	Nanjing	Zhengzhou	Hong Kong	Seoul	Singapore
RMSPE before T_0		0.03	0.04	0.07	0.07	0.18	0.15	0.08	0.4	0.09	0.02	0.02
Estimated reduction in February 2020		−0.96	−0.94	−0.88	−0.91	−0.92	−1.14	−0.96	−1.01	−0.51	−0.19	−0.06
Causal Impact Estimated reduction		−0.57	−0.55	−0.54	−0.53	−0.44	−0.74	−0.45	−1.10	−0.15	−0.09	−0.01
Straightforward reduction		−0.88	−0.82	−0.78	−0.82	−0.81	−1.00	−0.89	−0.87	−0.53	−0.10	−0.03
Infection rate in February 2020		19.50	13.95	21.92	29.56	8.44	4226.56	11.74	14.67	12.56	7.18	17.90
Unit	**Weights**											
Barcelona	0.00	0.00	0.00	0.00	0.00	0.00	0.57	0.00	0.00	0.00	0.00	
Boston	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Chicago	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Houston	0.32	0.00	0.00	0.00	0.00	0.00	0.15	0.00	0.00	0.14	0.06	
London	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.00	0.00	
Los Angeles	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.57	0.00	0.00	
Madrid	0.38	0.55	1.00	1.00	0.65	0.11	0.28	0.00	0.00	0.31	0.48	
Miami	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.21	0.18	0.13	
New York City	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	
San Francisco	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Washington D.C.	0.00	0.45	0.00	0.00	0.35	0.89	0.00	1.00	0.00	0.37	0.20	

Predictor balance	T	S	T	S	T	S	T	S	T	S	T	S	T	S	T	S	T	S	T	S	T	S
Fare	−0.8	0.3	−0.8	0.3	−1.3	0.0	−0.8	0.0	−0.6	0.3	−1.3	0.6	−1.3	0.2	−1.3	0.7	−0.1	0.5	−0.6	0.4	0.0	0.3
Population	16.9	15.7	17.0	14.7	16.6	15.7	16.4	15.7	16.6	14.9	16.2	13.7	16.0	15.6	16.2	13.5	15.8	15.8	16.1	14.7	15.6	15.1
GDP	9.9	11.1	10.0	11.0	10.1	10.9	10.3	10.9	9.6	11.0	10.0	11.1	10.1	10.8	9.7	11.2	10.8	11.2	10.6	11.0	11.2	11.0
Speed	3.6	3.2	3.6	3.4	3.6	3.4	3.5	3.4	3.6	3.4	3.5	3.5	3.9	3.3	3.5	3.5	3.4	3.3	3.4	3.4	3.4	3.4
Station	5.9	5.2	6.0	5.2	5.5	5.9	5.3	5.9	5.6	5.4	5.6	4.7	5.3	5.1	4.7	4.5	5.1	4.5	5.9	4.6	4.8	5.1
Age	3.9	4.0	3.3	4.2	3.1	4.6	2.7	4.6	2.3	4.3	2.7	3.9	2.7	4.3	1.9	3.8	3.7	3.8	3.8	3.9	3.5	4.2

*T-Treated unit; S-Synthetic control unit.
*Predictors are introduced in logarithm form.

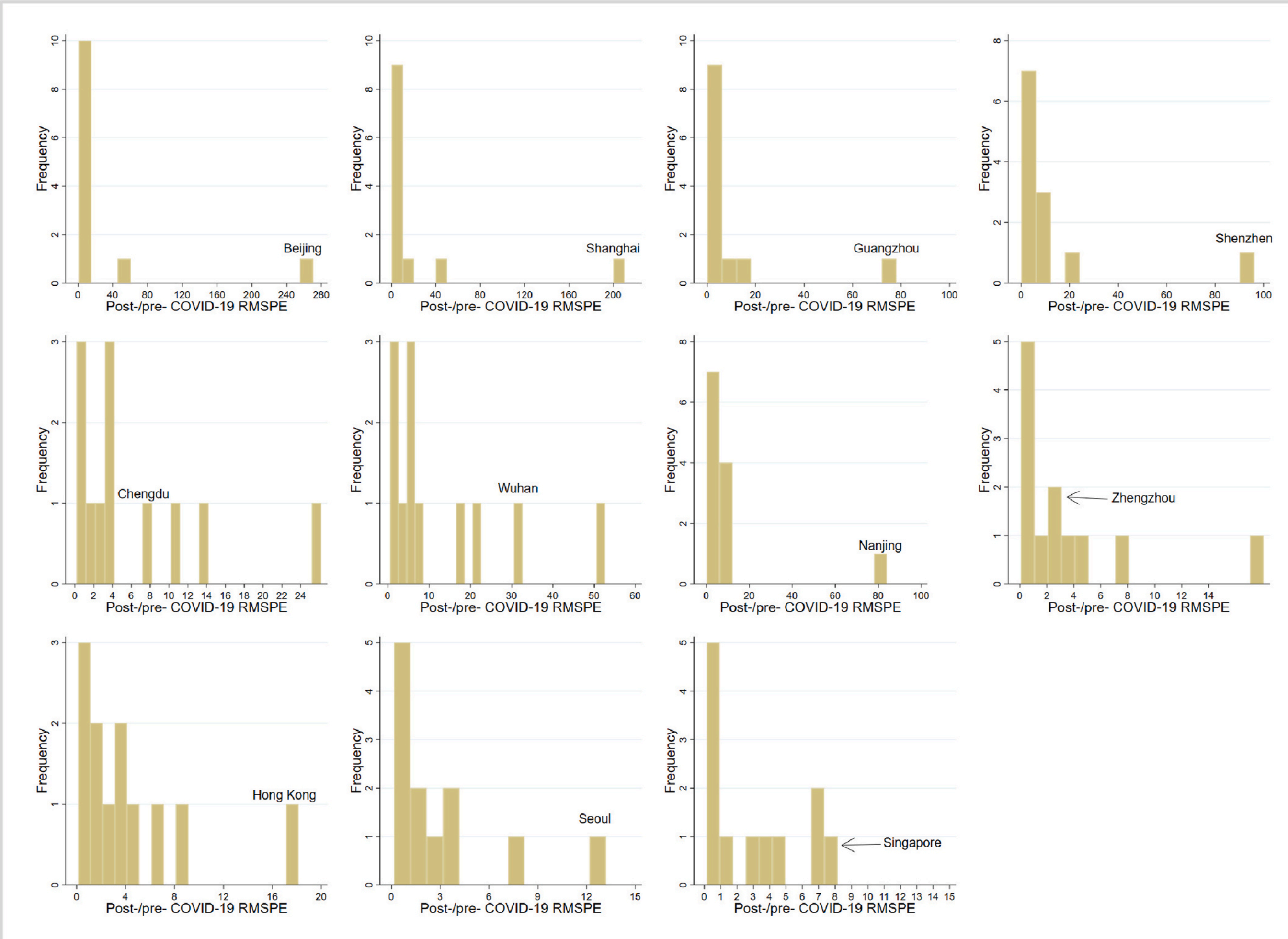

Fig. 7. Distributions of the ratio of RMSPE before and after COVID-19 for 11 cities.

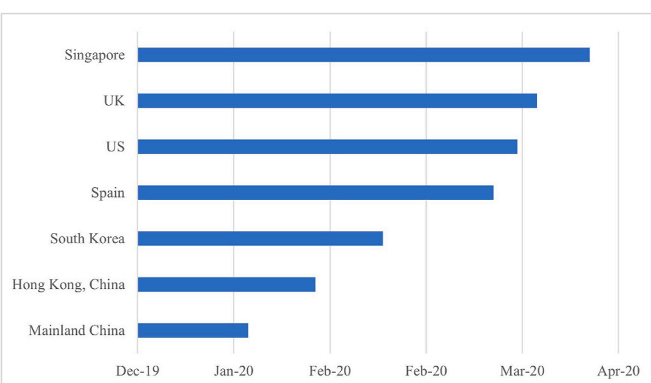

Fig. 8. Restricted dates by country.
*Data collection sources: Wikipedia, 2020.

travelling or selecting public transit. These conclusions can provide support for policymakers in terms of the lockdown period.

The potential control cities are Madrid, Houston, and Washington D. C. since these three gained weights for more treated cities, indicating that combinations of two of these cities can reproduce the relative change in daily ridership for the 11 cities of interest. Another five cities (Barcelona, London, Los Angeles, Miami, and New York City) also carried weights for different cities, thus assisting the potential control cities to generate a reasonable counterfactual outcome that perfectly fits the pre-intervention. Besides, Madrid is the only control city that gained weight in the SCM of Guangzhou and Shenzhen, which means that the relative change in daily ridership in Madrid was similar to that in Guangzhou and Shenzhen. Thus, it does not need to be combined with other cities.

A close match of predictors between the treated and synthetic units (shown in Table 2 as the predictor balance) would confirm the reasonable approximation of the synthetic control unit for the treated unit. The population, GDP, number of stations, and the operation speed were close between the treated and synthetic control units. However, the discrepancies of the system's age and fares are larger than other predictors (population, GDP, the number of stations, and the average operating speed). The URT systems characteristics between Asian and other cities can explain the discrepancy. It is challenging to generate a comparable age for the treated cities using the potential control cities because most control cities established their URT systems decades earlier than the treated cities. Besides, fares in Asian cities, collected in US dollars, have been much smaller than those in the US and European cities. These discrepancies can be of lesser concern since the synthetic control unit can closely track the relative change in daily ridership in most cities (Abadie, 2021). However, it is undeniable that these discrepancies could influence the optimization of the estimation because the predictor values for treated units fall close to but outside the convex hull of the predictor value for untreated units. Several methods have been proposed to overcome this problem, such as Bayes SCM, penalized SCM, and generalized SCM (Abadie and L'Hour, 2020; Doudchenko and Imbens, 2016). The penalized SCM is selected to further analyze the impact of

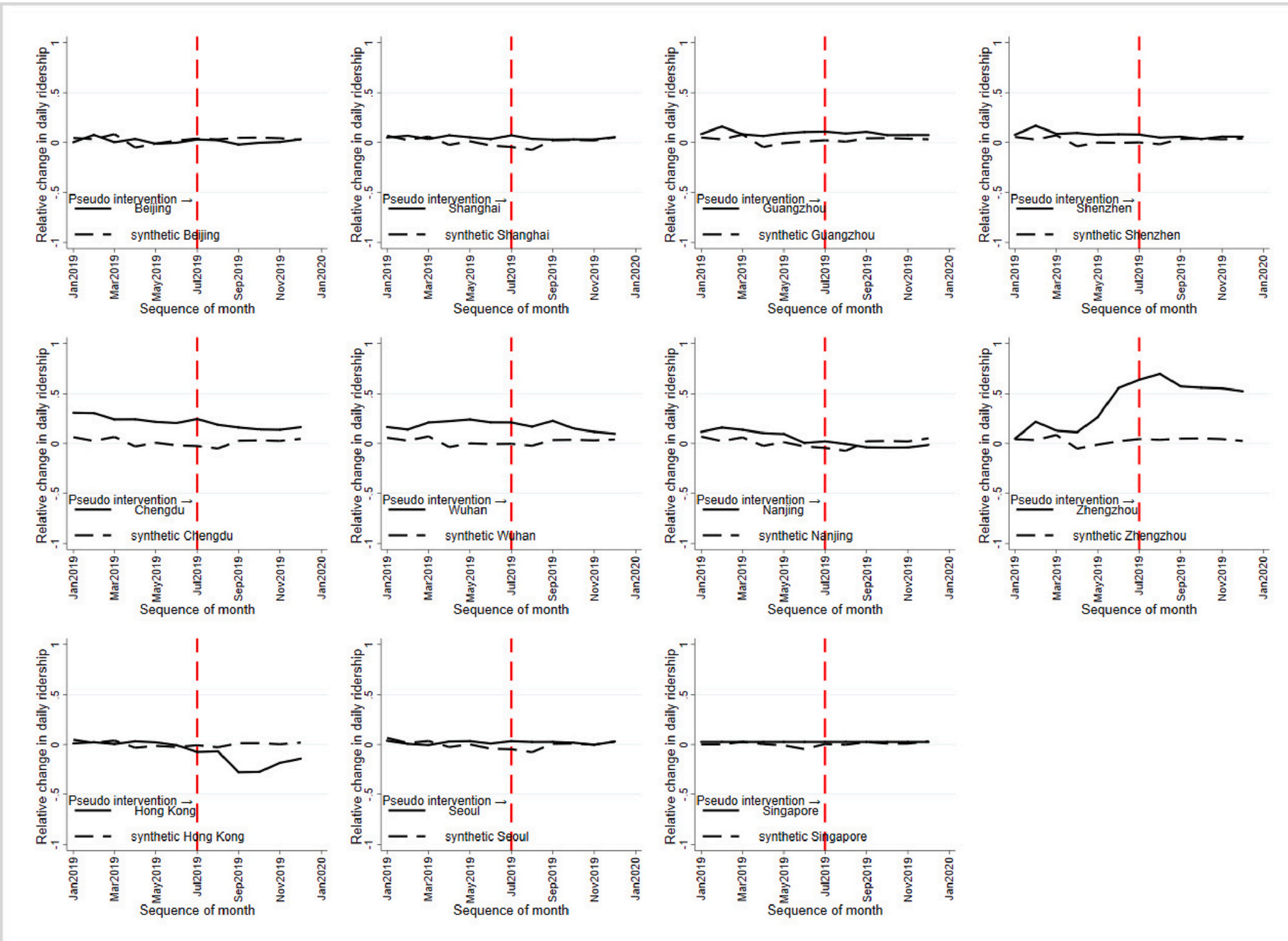

Fig. 9. SCMs for the 11 treated cities based on backdating intervention.

COVID-19 on URT ridership. The penalized SCM relaxes the convex hull by introducing a penalty term when estimating the weights. The R code ‘pensynth’ provided by Abadie (2020) is used to search for the optimal coefficient for the penalty term, lambda. According to the estimation results, the optimal lambda was zero. This means that the penalized SCM can generate the same synthetic control unit for the treated units as the pure SCM (employed in the present study). The pure SCM can generate the optimal solution for the treated cities. Thus, we use the pure SCM to investigate the effect of COVID-19 on URT ridership, ignoring any concern for the discrepancies between variables. Because this is not the primary focus of the study, a detailed analysis of this is not provided.

To further validate the credibility of the selected variable on URT ridership analysis, this study employs a backdating method proposed by Abadie (2020)to address the anticipation effects on the outcome variable before intervention occurs, which can be taken as the placebo test in terms of time. The backdating method divides the pre-intervention periods into an initial training period and subsequent validation periods, backdating the pseudo intervention to a time point before the COVID-19 pandemic. In this study, the data for January–June 2019is divided into the initial training period, and the data for July–December 2019is divided into the validation periods. The pseudo intervention is set as July 2019. The results of the backdating analysis are displayed in Figs. 9 and 10.

Figs. 9 and 10 display the SCM and placebo test results of estimating the effect of the pseudo intervention backdated to July 2019. The synthetic and treated curves show similar trends, with a stable trend before and after the pseudo intervention except for Chengdu, Wuhan, Zhengzhou, and Hong Kong. The results in the four excluded cities correspond with the imperfect synthetic controls in Figs. 5 and 6. Despite the placebo tests in the four cities, the gaps between the synthetic and treated curves are around zero before and after the pseudo intervention, as expected. Several important features can be indicated. First, the synthetic control outcomes fit closely the relative change in daily ridership in July–December 2019before the COVID-19 pandemic actually started in seven treated cities. This means that the controlled predictors can credibly generate a synthetic control outcome that reproduces the trajectory of the outcome in the treated unit because the estimated counterfactual outcome is close to the observed outcome. Second, there is no visibly large gap between the treated and synthetic control curves, despite the pseudo intervention backdated in July 2019. This demonstrates that the synthetic control can reproduce the outcome for the treated unit under the “in-time placebo test” (Abadie et al., 2015).

This study employs two other traditional methods (straightforward analysis and causal impact analysis) to re-estimate the URT ridership reduction after the outbreak of COVID-19 in the 11 treated cities to illustrate the usefulness of the SCM. Straightforward analysis, which estimates the effect of an intervention by comparing differences in the outcome between the current and previous year, was selected for comparison because it is a traditional method for the analysis of time-series data. The causal impact analysis is another method used to estimate counterfactual outcomes of a treated unit, which has a similar idea to the SCM. Thus, it was selected to illustrate the usefulness of the SCM. The fifth and sixth columns in Table 2 display estimation results of the two

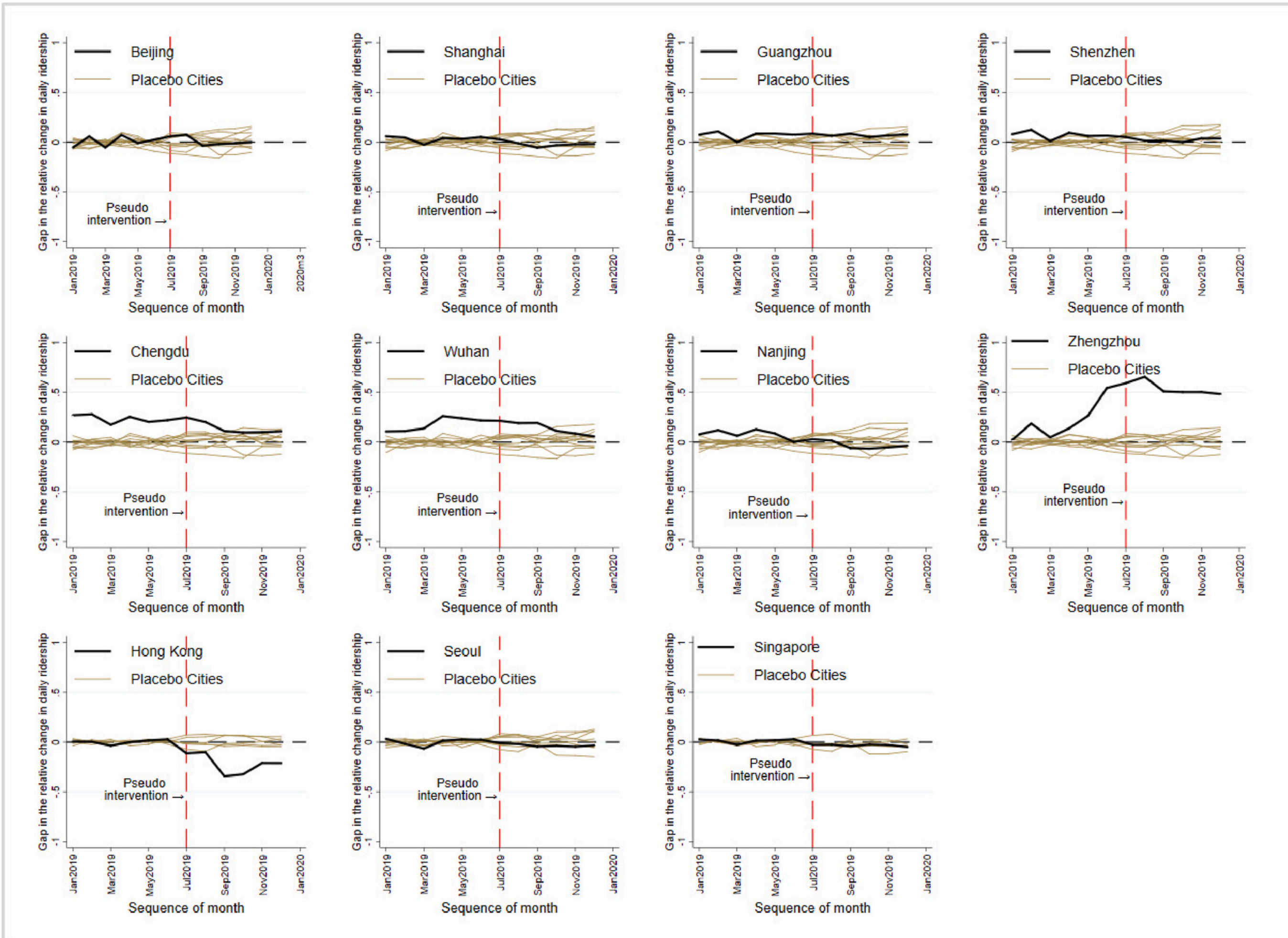

Fig. 10. Placebo tests for the 11 treated cities based on backdating intervention.

methods.

The causal impact analysis is conducted in R 4.0.5 using the package "CausalImpact" (Brodersen et al., 2015). The estimated ridership reductions by the causal impact analysis are lower than those estimated by the SCM, except the results for Zhengzhou; this is understandable given the principle of causal impact analysis. Causal impact analysis estimates a counterfactual outcome using covariates that were not affected by the intervention rather than the weighted outcome of control units. However, for the COVID-19 pandemic, for the covariates, which meet these requirements, it was challenging to generate counterfactual outcomes because most remained stable in the long term. This means that the dynamics of the outcome can be neglected and not comprehensively captured by the covariates. Thus, a lower reduction was estimated in most cities. Regarding the reverse case in Zhengzhou, there is a considerable increase in the relative change in daily ridership before the outbreak of COVID-19, which can influence the estimation of SCM. The estimated effects in the straightforward analysis are also lower than those by the SCM, except in Hong Kong. The straightforward analysis can reasonably interpret the reduction in URT ridership when it remains stable from year to year. However, the URT ridership changes dynamically, especially in most Chinese cities. According to a report published by the China Association of Metros (2019), URT ridership has increased recent prior to 2019. Thus, it is not reasonable to use a straightforward comparison to analyze any reduction in ridership. The demonstrations in Hong Kong led to a ridership reduction before the outbreak of COVID-19, which influenced the estimated results of SCM. Therefore, in the case of COVID-19 impacts, the SCM demonstrate its usefulness for estimating the effect of COVID-19 on ridership compared with other methods.

4.2. Extending the SCM application: effects of system closure in wuhan

The URT system of Wuhan closed on January 23 and reopened on March 23. Therefore, the application of SCM is extended to estimate the effects of the system closure on ridership recovery.

Suppose that the effect of the system closure on ridership recovery in Wuhan can be estimated with the aid of the control cities which were also exposed to the COVID-19 but did not close the system. Then the observed outcome Y_{jt} can be written as three parts, the potential outcome is determined by the predictors (Y_{jt}^{N}), the estimated effects of COVID-19, $\alpha_{jt}^{COVID-19}$, and the estimated effects of system closure, $\beta_{jt}^{system\ closure}$, defined as

$$Y_{jt} = Y_{jt}^{N} + \alpha_{jt}^{COVID-19} D_{jt}^{COVID-19} + \beta_{jt}^{system\ closure} D_{jt}^{system\ closure} \tag{8}$$

where $D_{jt}^{COVID-19}$ is a dummy variable with value of 1 for the unit affected by the outbreak of COVID-19 and 0 otherwise; $D_{jt}^{system\ closure}$ is a dummy variable with value of 1 for the unit which closed its URT system and 0 otherwise. $\beta_{jt}^{system\ closure}$ can be estimated if we assume that the $\alpha_{jt}^{COVID-19}$ is equal for the treated city and potential control cities. According to Fig. 4, there is a 90% reduction approximately in daily ridership for the seven considered cities (Beijing, Shanghai, Guangzhou, Shenzhen,

Table 3
SCM details and predictor balance for Wuhan.

Treated unit	Wuhan					
RMSPE before T_0	0.04					
Unit weights	Beijing	0.28	**Predictor balance**	**Predictors**	**Treated**	**Synthetic**
	Shanghai	0.00		fare	−1.27	−1.10
	Guangzhou	0.00		population	16.25	16.31
	Shenzhen	0.63		GDP	9.99	10.06
	Chengdu	0.09		Speed	3.47	3.76
	Nanjing	0.00		stations	5.62	5.50
	Zhengzhou	0.28		age	2.75	3.08

* Predictors are introduced with logarithm form.

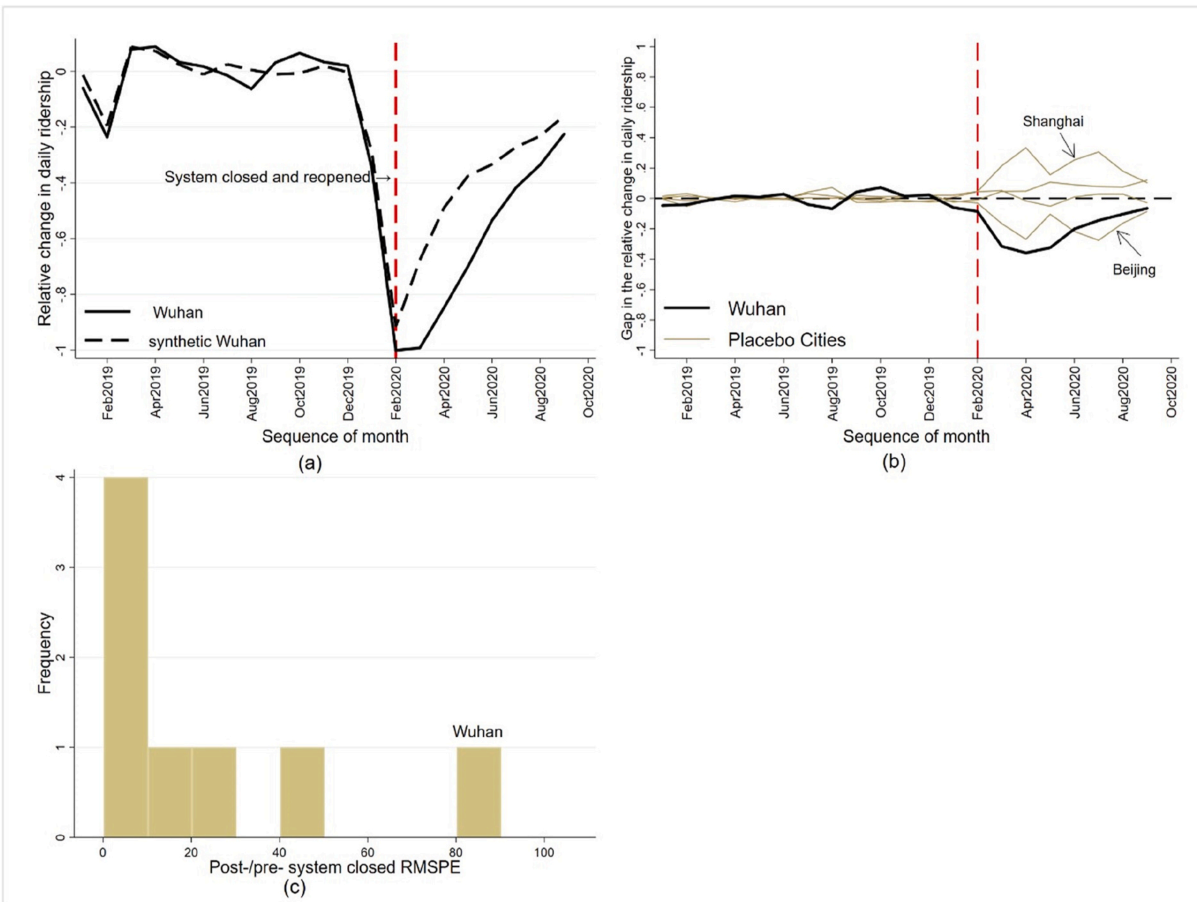

Fig. 11. SCM and placebo test results for Wuhan.

Chengdu, Nanjing, Zhengzhou). The ratio of RMSPE before and after COVID-19 for Hong Kong, Seoul, and Singapore is not obviously large. Therefore, the former seven cities are considered as potential control cities.

Under this assumption, the treated period is February 2020, the treated unit is Wuhan. Table 3 provides the fitted details. Fig. 11 displays the SCM results and distribution of the ratio of RMSPE.

Table 3 illustrates the efficiency of the SCM. Four cities (Beijing, Shenzhen, Chengdu, and Zhengzhou) in the control group are assigned positive weights while all others receive a weight of zero. The differences between the predictor values of the treated and synthetic units are smaller than those in Table 2, indicating that the potential control cities from the same region have a larger power to generate the synthetic unit for the treated city. However, the disparity in the system's age is larger than the other five predictors. The synthetic control curve in Fig. 11-a represents the tendency for the relative change in daily ridership if the system had not closed in February 2020, distinct from the treated unit curve after the system closed and reopened. The treated unit curve is clearly under the synthetic control unit, indicating the slower recovery compared to the scenario if it had not closed. Besides, the curve's slope after the system closed and reopened is smaller than after the spring festival in February 2019, indicating the slower recovery speed. It is estimated that ridership would be 22% higher if there was no system closure in Wuhan. The gap in Fig. 11-b for Wuhan and the control cities indicates the system closure effect. Wuhan's gap is visibly larger than the cities that did not close their URT system during the recovery period after the system closed and reopened in February 2020. Shanghai's curve is obviously larger than zero, which means that its ridership level was already above their average daily ridership in 2018. However, Beijing's curve is under the x-axis, which indicates Beijing's URT ridership's slow recovery speed. One potential reason is that Beijing's URT restrictions are stricter than other cities. Besides, the second wave of

COVID-19 at the end of June 2020 in Beijing hit the URT ridership, and thus delayed the ridership recovery (Dong et al., 2020). The difference between the brown curve for cities in the control group and the black curve for Wuhan reveals the slow step of Wuhan's ridership recovery. The RMSPE ratio has the largest value for Wuhan compared to other control cities, thus confirming the expected effect of system closure on ridership recovery.

5. Conclusions

Based on the SCM proposed by Abadie et al. (2010), this paper demonstrates the negative effects of COVID-19 on the URT daily ridership change in 11 Asian cities (the majority of which from China) utilizing data from other cities around the world, primarily the US. The delay of the outbreak of COVID-19 in the US and other western countries provides ideal control samples for the application of the SCM. The negative impacts of the pandemic on the relative change in daily ridership in seven cities are confirmed according to the SCM results. The SCM results in four cities (Chengdu, Wuhan, Zhengzhou, and Hong Kong) did not yield meaningful results. The estimation significance is evaluated using a series of placebo tests to control cities and times for the 11 cities in the potential control group. The results show that the net effect of COVID-19 on URT ridership in seven Chinese cities was in the range of 85%–95%, larger than that in Hong Kong, Seoul, and Singapore, which had the net effects of 51%, 19%, and 6%, respectively. The estimated impact of COVID-19 on URT ridership diversity from the treated cities indicates that the duration and severity of the restrictions and lockdowns are associated with ridership reduction.

The results indicate several vital conclusions. First, the effects of COVID-19 on URT ridership reduction are not associated with the infection rate since some Chinese cities experienced a more considerable ridership reduction but a lower infection rate than others. Second, longer lockdowns and stricter restrictions can lead to a greater ridership reduction under the assumption of similar health risks perceived by citizens. URT ridership in Chinese cities that took timely actions with severe restrictions after the outbreak of COVID-19 experienced a visibly larger reduction than that in Seoul and Singapore, which adopted rapid and extensive testing instead of further lockdowns during the pandemic. This means that policymakers needed to make a trade-off between the URT ridership reduction and health protection. Governments and agencies played an essential part in determining URT ridership during the pandemic based on their restrictions. Timely and reasonable response adopted by governments and agencies were necessary during the pandemic. As such, these conclusions are meaningful for policymakers. Generally, policymakers implemented restrictions and lockdowns according to the number of confirmed cases. However, since the URT ridership reduction is associated with restrictions and lockdowns, lessons from other cities should be carefully considered. For example, the implemented measures in Seoul maintained ridership numbers; despite a significant increase in the number of new infections occurring in August 2020. While the severe restrictions in most Chinese cities controlled the spread of infections very well, ridership was greatly reduced.

In addition, an extended application of the SCM method was performed to estimate the effects of system closure in Wuhan on ridership recovery in the city. In this analysis, Wuhan is the treated unit, while seven other cities in China are selected as the potential control cities. According to the SCM results, the gap of Wuhan is relatively larger than those of the cities that did not close their URT systems. Because of the influence of the system closure, the recovery of Wuhan did not reach the expected level as shown in the synthetic control unit, as the treated unit curve is persistently under its synthetic control unit, indicating that system closure caused a slower recovery in Wuhan, by about 22%. From a policy perspective, the conclusions of this study could provide transit agencies with support and guidance on the net effects of COVID-19 on ridership reduction and the likely consequences of system closure on ridership recovery.

The usefulness of the SCM to estimate the effects of COVID-19 on ridership was demonstrated by comparing the estimation results with those of two other methods: causal impact and straightforward analyses. For both methods, it was challenging to obtain a reasonable estimation of the counterfactual outcome due to their inherent limitations pertaining to the case of COVID-19. In contrast, the SCM uses a data-driven method to generate a weighted average of outcomes in control units; thus, it is less affected by the absence of service-related attributes when estimating the counterfactual outcome. Furthermore, two other characteristics of SCM are ideal in the case of COVID-19. First, the SCM could estimate the effects of COVID-19 on ridership reduction for each treated unit, thus allowing the ridership reduction across cities to be compared. The associations between COVID-19 restrictions and ridership reduction are evidence of this. Second, the SCM could estimate the effects over a long period. In the present study, this can be reflected by the estimation of the impact of system closures on Wuhan's URT system. Other estimation methods, like the DID model, can only obtain the average effects pre- and post-intervention. Thus, SCM provides an appropriate method of estimating ridership reduction in the case of COVID-19. However, there is currently little guidance on the practical implementation of SCM in ridership analysis. The implication of SCM across 11 cities in this paper can fulfill the relevant research.

Although this study confirms and quantifies the negative effects on ridership due to the COVID-19 pandemic, further analysis is required to extend the research of this study and address its limitations. For example, the predictors in this paper are somewhat limited, and they exhibit discrepancies between the treated and synthetic control units. They were selected empirically according to previous studies. Other factors (e.g., land use attributes and the availability of other modes) that can influence ridership reduction during the pandemic should be added to strengthen the counterfactual outcome's interpretability. Besides, the system's closure that was investigated in this study is a network-level strategy; investigating such effects at the station and route levels would be meaningful since several agencies partially closed their URT systems for specific routes or stations. These analyses would help transit agencies formulate reasonable policies to minimize ridership loss. Finally yet importantly, the SCM can only estimate the effect of an individual intervention. In a practical study, there might exist several interventions that simultaneously affect the outcome, which would challenge the application of the SCM, (e.g. the outbreak of COVID-19 together with the flu season in US). It should be noted that the ridership reduction in the case of COVID-19 is also a combination result of several causations (infections, health risks perceived by citizens, severity and duration of different restrictions), but the potential influence of the perceived health risks and infections were excluded while combining the related research and the results in this study. Admittedly, this paper provides an analysis based on the results and samples in the 11 covered Asia cities; however, the effect of different severity and duration of restrictions on URT ridership in the US and Europe cities should be studied carefully in the future.

Author contributions

The authors confirm contribution to the paper as follows: study conceptualization and formal analysis: Amer Shalaby and Mengwei Xin; data curation: Mengwei Xin, Amer Shalaby, Shumin Feng, Hu Zhao; methodology and investigation: Mengwei Xin and Amer Shalaby; writing-original draft: Mengwei Xin, Amer Shalaby. All authors reviewed the results and approved the final version of the manuscript.

Declaration of competing interest

The authors declare that there is no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tranpol.2021.07.006.

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