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Invited Research Paper

Improving the subway attraction for the post-COVID-19 era: The role of fare-free public transport policy

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ABSTRACT

Coronavirus disease 2019 (COVID-19) has had a disruptive impact on transportation. To prevent a return to more widespread personal automobile use due to social distancing requirements, public transport should regain its critical role in carrying a large number of passengers. To this end, three Chinese cities, Hangzhou, Ningbo, and Xiamen, implemented fare-free policies to lure passengers back to public transport. To capture the effect of these policies implementation on the daily subway passenger flow, a synthetic control method is used to construct a counterfactual outcome of interest for these three cities. The results show that the peak-hours free-ride policy in Hangzhou had no significant effect on subway ridership, the “more rides, more discounts” and off-peak-hours free-ride policies in Ningbo increased subway ridership by about 24% in the first month, and a rest day free-ride policy in Xiamen increased subway ridership by 2.3 times over five rest days. Nevertheless, the role of the fare-free policies in helping subway ridership rebound to the historical levels is limited, whether it is during or after policy implementation. Findings of the current study can inform the local authorities and transport operators that the multi-pronged approaches should be implemented in tandem with the fare-free policies for increasing subway attraction during the recovery phase of the COVID-19 pandemic.

1. Introduction

Coronavirus disease 2019 (COVID-19) is having huge impacts around the world, rocking financial markets, increasing unemployment, popularizing telecommuting and online learning, cutting down flights and personal travel, and affecting mental health and well-being. To contain the spread of COVID-19, many countries have declared a national emergency and issued stay-at-home orders. As people are forced to quarantine, some unintended benefits have appeared, such as improved air quality and cleaner water. In China, nitrogen dioxide levels have plummeted by as much as 30% during the peak of the pandemic, according to the National Aeronautics and Space Administration (Sommer, 2020). As infections and deaths have declined, various cities have gradually eased their lockdown restrictions. However, certain traffic problems reappear when companies and factories are braced for revitalization. First, public transport ridership has fallen by 50–90% in many places (Welle and Avelleda, 2020). This decreased ridership could sharply cut revenue and scale back services. In addition, road traffic is gradually increasing. In the first quarter of 2020, traffic congestion in some cities has become worse than that of the same period last year, even before full work resumption has been fully achieved (Baidu Map, 2020). A recent survey by the Energy Resources Institute also found that 35% of commuters are likely to change their mode of commuting after the COVID-19 lockdown is lifted, which indicated the largest decrease in metro services and buses (Venkatraman, 2020). Therefore, less use of public transport is inevitable in the post pandemic environment without any intervention.

To curb the trend toward more congested roads and emptier public transport, three Chinese cities have introduced different types of fare-free public transport policies to lure passengers back. Hangzhou implemented a peak-hours free-ride (PHFR) policy from March 18 to March 31, 2020. Bus lines (except special lines) and subway lines were free for passengers during weekday morning and evening peak hours (7:00–9:00 and 16:30–18:30). Ningbo implemented a “more rides, more discounts” (MRMD) policy from March 23, 2020. MRMD meant that a certain number of free subway e-tickets would be distributed to passengers during a discount period (i.e., 30 days) when subway use and the monetary consumption of these passengers met certain thresholds. These free subway e-tickets could be used for trips of any distance and departure time. Furthermore, Ningbo introduced an off-peak-hours free-

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ride (OPHFR) policy from March 31 to May 6, 2020. The subways were free of charge during off-peak hours, whether on weekdays, weekends, or holidays. A rest day free-ride (RDFD) policy was in effect in Xiamen from April 11 to June 30, 2020. Citizens and tourists could take the subway, bus rapid transit (BRT), and buses for free on both statutory holidays and rest days. The policies implemented in these three Chinese cities are tentative interventions. Whether they can truly revive public transport after the pandemic is an open question.

Although fare-free public transport policies are uncommon in real-world cases, a few successful ones still exist in parts of European cities, Estonia, remote cities in China, and the United States (Hess, 2017). Several field experiments have also demonstrated that fare-free public transport policies are effective in increasing public transport use (Fujii and Kitamura, 2003; Bamberg et al., 2003; Thøgersen and Møller, 2008). To evaluate the effect of the implementation of these policies, a before-and-after comparison method is generally adopted (Goeverden et al., 2006; Brand, 2008; Kębłowski, 2018; Thøgersen and Møller, 2008). However, statistical analyses are limited to descriptive measurements and variance analysis. The choice of analysis technology should be theoretically grounded. In addition, individuals' response to the policy implementation usually takes place in a stable decision context, although one study considered policy effect under new circumstances (Bamberg et al., 2003). Against the background of the influenza pandemic, little is known to what extent fare-free public transport policies affect ridership. In the end, comparisons between the fare-free public transport policies, which limited to different certain service time, are scarce.

To explicitly capture the effects of the implementation of a fare-free public transport policy on ridership, this study focused on daily subway passenger flow changes. Subway ridership was chosen as the outcome of interest because three different types of fare-free transport public policies all applied to the subway, and because the available data are limited. Given that the policies examined in three Chinese cities are non-targeted and affected all residents, a novel approach, namely the synthetic control method (SCM), was used to construct counterfactual scenarios for Hangzhou, Ningbo, and Xiamen. Hence, the impacts of different fare-free public transport policies on subway ridership could be assessed and compared. Through our findings, we contributed to the literature that explores the extent to which free public transport policies promote ridership. Our analysis also provided some evidence that individuals react differently to different types of fare-free public transport policies. Therefore, this study provides timely support for policy-making, and facilitates the public transport ridership back to pre-pandemic levels.

The remainder of this paper is organized as follows: Section 2 reviews recent and relevant studies of fare-free public transport polies. Section 3 explains the research method and related data. Sections 4 and 5 present and discuss the empirical results. After that, final section concludes the study and suggests directions for future research.

2. Literature review

Policy interventions that make public transport more attractive than other modes of transport can effectively increase ridership (Vigren and Pyddoke, 2020). On the one hand, more attractive and convenient public transport services can be obtained by measurements (e.g., public transport fare adjustment and public transport priority). On the other hand, charging and regulations, such as road pricing, parking fee increases, and vehicle restriction policies, increase the costs of driving, thereby contributing to a higher level of public transport ridership. However, raising the cost of driving is likely to generate psychological and political resistance, especially in the difficult period of the coronavirus pandemic. For that reason, some Chinese cities have piloted fare-free public transport policies at the post-COVID-19 phase to shift traffic demand from automobiles toward public transport.

Fare-free public transport policies are not common, as they are associated with a high financial burden and service quality challenges. Originally, the effect of fare elimination on ridership is assessed by fare elasticity (Cervero, 1990). As previously discussed, the industry standard has set fare elasticity at −0.3 (Hodge, Orrell III and Strauss, 1994). However, the experience of real-world cases has seen more impressive increases in ridership (Table 1). In recent decades, a few real-world cases have been evaluated to examine the effects of fare-free public transport policies. In 2004, bus lines between Leiden and The Hague were free for everyone Mondays through Fridays (Goeverden et al., 2006). The authorities sought to reduce road congestion by offering an alternative travel mode for commuters. Goeverden et al. (2006) concluded that ridership on these free bus lines tripled. However, there was little evidence showed that congestion eased, and the shift from cars to public transport partly took place in off-peak hours.

Another well-known case is the free-fare public transport in Hasselt. Before the inception of the free public transport policy, the public transport system was inconvenient and unpopular. Making the bus free, together with an improved network and better service quality, proved to be a landmark, as a ninefold increase in ridership occurred in the first year (Brand, 2008). Moreover, 37% of the additional trips came from new users, of whom 16% had switched from cars, 12% from bicycles, and 9% from walking (Goeverden et al., 2006). Although the change indicated success for fare-free public transport policy, merely 5% of trips were made by bus in 2013, which provides a more objective critique (Cats et al., 2017). The era of free public transport ended in 2013 due to the extraordinarily rapid growth in cost.

Among at least 20 French cities that have abolished fares for public transport, Aubagne and nearby municipalities are the most well-known. Kębłowski (2018) argued that ridership increased by about three times in seven years, and the vulnerable groups, in particular youth, the elderly, and single mothers, benefited most from the fare-free public transport policy. In terms of travel mode shift, Kębłowski (2018) also concluded that half of new public transport travelers used to rely on private cars or motorcycles.

Fare abolition has also been applied to larger urban areas. Tallinn, the capital of Estonia, introduced a fare-free public transport policy in 2013 to promote public transport, enhance mobility, and increase municipal tax income. Using automated vehicle location and automatic passenger count data, Cats et al. (2014) employed a multivariate analysis to investigate the effects of the policy. The results show that the policy led to a 1.2% increase in ridership for the first four months of operation. Furthermore, Cats et al. (2017) evaluated the changes before and almost a year after the policy was implemented using an annual municipal survey. The market share of public transport increased by 14%, which came from a 10% decrease in car trips and a 40% decrease in trips for which walking was the main travel mode. Moreover, the younger age group (15–19), the older age group (60–74), and the low-income group dramatically increased their public transport usage. It is noteworthy that while trips successfully shifted from automobiles to public transport, vehicle miles traveled increased by 31%.

Besides the above real-world cases, there are some other forms of fare-free public transport policies, focusing on the category of passenger or certain periods of the day (De Witte et al., 2006; Perone, 2002). Considering the limited number of real-world cases, some researchers have conducted field experiments in which a sample were given a free public transport ticket for a short term. Then, the effect of the fare-free public transport policy could be obtained by measuring the differences between reported travel behaviors before, during, and after the intervention (Friman et al., 2019; Thøgersen, 2009; Abou-Zeid and Ben-Akiva, 2012) or by comparing the study group with a control group (Fujii and Kitamura, 2003; Bamberg et al., 2003; Beale and Bonsall, 2007). Compared with real-world cases, these studies are more economic friendly, targeted to a certain group of people (e.g., car owners), and provide a convenient way to answer a broad range of questions, such as how individuals' psychological factors and satisfaction change. However, self-selection bias or the lack of randomized control groups

Table 1
Studies of real-world cases of fare-free public transport programs.

Location (Time span)	Targeted group	Time of day	Scope of fare-free public transport	Results	References
Leiden and The Hague (January–December 2004)	Everybody	All day from Monday to Friday	3 bus lines	Ridership on free bus lines increased from 1,000 to 3,000 passengers a day. Congestion was not eased.	Goeverden et al. (2006)
Hasselt, Belgium (July 1997–April 2013)	Everybody	All day from Monday to Sunday	9 bus lines	Ninefold increase in ridership in the first year.	Brand (2008), Goeverden et al. (2006)
Aubagne and nearby municipalities, France (2009–)	Everybody	All day from Monday to Sunday	11 regular bus lines, 13 school bus lines, and a tram line	Ridership increased by about three times in seven years.	Kębłowski (2018)
Tallinn, Estonia (2013–)	Registered Tallinn residents	All day from Monday to Sunday	Buses, trolley buses, and trams	Ridership increased by 1.2% for the first four months of operation. Public transport's share increased by 14%. Vehicle miles traveled increased by 31%.	Cats et al. (2014), Cats et al. (2017), Hess (2017)

may be an issue in these studies, and larger-scale experiments may be more appropriate.

There is a general consensus among the previous studies about the promotion effect of fare-free public transport policies in increasing ridership. However, the preceding evaluations of the effects of these policies have some limitations due to the disadvantage of before-and-after comparisons and the lack of available control groups, thereby threatening the validity of the inferences derived from the results. Detailed and systematic analyses of fare-free public transport policies are desperately needed. To fill this gap, this study employed a SCM to construct a valid counterfactual, thereby facilitating a contemporaneous comparison. The SCM has been widely used in causality and policy evaluations, and has overcome the identification problem. The promotion effects of a fare-free public transport policy can be divided into generation effects and substitution effects, which makes sense when individuals are in a stable decision context. In the shadow of a pandemic, however, it is difficult to say whether people will forgo private transport or generate unnecessary travel due to subway fare abolition. It would be premature to conclude that fare-free public transport policies influence individuals' public transport use during the post-pandemic period. Besides, the published studies scarcely distinguish the influence of fare-free public transport policies in different periods of the day or different days of the week. In this study, the three real cases, using different fare-free public transport policies, will be assessed and compared to enhance the understanding of the role of fare elimination.

3. Research method and data

3.1. Synthetic control method

To investigate the effects of fare-free public transport policies on subway attraction, a SCM was used in this study. The SCM can conduct a counterfactual analysis and evaluate how a treatment (e.g., a policy) can affect the outcome variable of interest (e.g., daily subway passenger flow). As proposed by Abadie et al. (2010), SCM postulates that the counterfactual of the treated city, which is also called the synthetic city, can be obtained by calculating the weighted average of non-treated cities. During the pre-treatment period, the observed outcome variable of the treated city should match that of the synthetic city. After the policy implementation occurs, the treatment effect can be explained by the difference between the trends for the outcome variable in treated city and synthetic city. SCM has certain advantages over other more widely used methods. First, when the treatment is non-targeted and affects the entire city, a limited number of control groups are available (Abadie et al., 2015). Moreover, the valid choice of control groups is one of the challenges of comparative case studies. The SCM uses a combination of control groups to provide a better comparison of the city affected by the policy than any individual city (Abadie et al., 2010). Second, the SCM relaxes the parallel trends assumption and accounts for observed and unobserved time-varying effects (Bouttell et al., 2018). Finally, SCM estimators are valid both externally and internally (Olper et al., 2018). Therefore, the SCM is a suitable approach for the comparative case studies in the present study.

The principle specific to the SCM is as follows: suppose a panel of $J+1$ cities over T periods, $j=1$ is the treated city that implemented fare-free public transport policy at time T_0, and $j=2,3,\ldots,J+1$ are control groups that have not been affected by the policy. PF_{jt} indicates the observed daily subway passenger flow for city j at time t. For city $j=1$ and time periods $t=1,\ldots,T$, PF_{jt}^N represents the daily subway passenger flow that would be observed at time t if a fare-free public transport policy had not been implemented in the treated city. After the treatment implements, the treatment effect for the treated city at time $t>T_0$ is given as follows:

$$\alpha_{jt}=PF_{jt}-PF_{jt}^N \tag{1}$$

The goal of this study is to estimate the vector of dynamic treatment effects $(\alpha_{j,T_0+1},\ldots,\alpha_{j,T})$. Hangzhou, Ningbo, and Xiamen instituted fare-free public transport policies after period T_0, and the real daily subway passenger flow can be observed. However, the potential daily subway passenger flow in these cities without the impact of the fare-free public transport policies cannot be observed. Therefore, a factor model is used in the SCM to identify the potential counterfactual PF_{jt}^N:

$$PF_{jt}^N=\delta_t+\boldsymbol{\theta}_t\boldsymbol{Z}_t+\boldsymbol{\lambda}_t\boldsymbol{\mu}_t+\varepsilon_{jt} \tag{2}$$

where δ_t is an unknown common term and has same impact on all cities; $\boldsymbol{Z}_t$ is an $(r\times 1)$ vector of the control variable that is not affected by the fare-free public transport policy, $\boldsymbol{\mu}_t$ is an $(F\times 1)$ dimensional unobserved fixed effect, $\boldsymbol{\theta}_t$ and $\boldsymbol{\mu}_t$ are vectors of unknown parameters to be estimated, the error term ε_{it} is unobserved temporary impacts, and $\mathrm{E}(\varepsilon_{it})=0$.

To evaluate the influence of fare-free public transport policies on daily subway passenger flow, a suitable solution is to simulate the characteristics of the studied city by weighting the control group in a donor pool: assuming a $J\times 1$ vector of weights $\boldsymbol{W}=(\omega_2,\omega_3,\ldots,\omega_{j+1},)$, satisfied $\omega_j\geq 0$ and $\omega_2+\omega_3+\ldots+\omega_{j+1}=1$. Each specific value of vector $\boldsymbol{W}$ is a particular weight for each city in the donor pool. Therefore, the synthetic value of the outcome variable is as follows:

$$\sum_{j=2}^{J+1}\omega_jPF_{jt}=\delta_t+\boldsymbol{\theta}_t\sum_{j=2}^{J+1}\omega_j\boldsymbol{Z}_j+\boldsymbol{\lambda}_t\sum_{j=2}^{J+!}\omega_j\boldsymbol{\mu}_j+\sum_{j=2}^{J+1}\omega_j\varepsilon_{jt} \tag{3}$$

Suppose there is a vector group $\boldsymbol{W}^* = (\omega_2^*, \omega_3^*, \ldots, \omega_{j+1}^*)$ satisfying

$$\sum_{j=2}^{J+1}\omega_j^* PF_{j1}=PF_{11},\sum_{j=2}^{J+1}\omega_j^* PF_{j2}=PF_{12},\ldots,\sum_{j=2}^{J+1}\omega_j^* PF_{jT_0}=PF_{1T_0}\, and \sum_{j=2}^{J+1}\omega_j^*\mathbf{Z}_j=\mathbf{Z}_1. \tag{4}$$

To obtain the vector $\boldsymbol{W}^*$, the pre-treatment root mean squared prediction error (RMSPE) is minimized:

$$\min RMSPE_i = min\sqrt{\frac{1}{T_0}\sum_{t=1}^{T_0}\left(PF_{1t}-\sum_{j=2}^{J+1}\omega_j^* PF_{jt}\right)^2} \tag{5}$$

where PF_{1t} is the observed daily subway passenger flow of the treated city in pre-treatment period. $\sum_{j=2}^{J+1}\omega_j^* PF_{jt}$ is the weighted average of untreated cities, which represents the counterfactual outcome of the treated city in period t. Once the vector W^* is determined, the effect of the policy can be evaluated using Eq. (1). Details about the computational process and discussion can be seen in Abadie et al. (2010) and Abadie et al. (2015).

3.2. Data

In this study, city-level data on daily subway passenger flow were chosen as the outcome variable. Hangzhou, Ningbo, and Xiamen were the treated group, and 19 first-tier or new first-tier cities in China were the potential donor pool for the SCM. To avoid the overfitting problem, it is important to abandon some control cities, which differ from the treated cities in their main characteristics (Abadie et al., 2015). First, Beijing and Shanghai are excluded because they are China's political and economic centers and are regulated differently from other cities. Second, Wuhan is also excluded as it suffered the worst losses and recovered the slowest over the pandemic period compared to other cities. Moreover, it is worth noting that vehicle restriction policies have been used in many Chinese cities to address the externalities of private road traffic. This helps to increase subway passenger flow by increasing the cross-elasticities of car drivers switching to public transport (Vigren and Pyddoke, 2020). Therefore, a city is not included in the possible donor pool of a treated city if the given control city and treated city have different requirements as to whether to implement vehicle restrictions before or after the pandemic outbreak. In the Hangzhou context, Chengdu, Guangzhou, Shenzhen, Tianjin, and Xi'an are included in the donor pool. Prior to the coronavirus outbreak, Hangzhou and its donor pool had implemented vehicle restrictions. It was not until March 30, 2020, that some cities began to resume the restriction on cars. The other eight Chinese cities (Changsha, Chongqing, Dalian, Dongguan, Nanjing, Qingdao, Shenyang, and Suzhou) belong to the donor pool of Ningbo and Xiamen, as this donor pool and the two treated cities never issue restrictions on vehicle usage.

The control variables selected in this study include the rate of work resumption in the four weeks before the policy was implemented, the daily subway passenger flow from January 1 to January 19, 2020, and the log of per capita gross domestic product (GDP). When the government guides individuals to return to normal life in a manageable way, travel intensity is closely related to the pace of the city's resumption of work, as this generates some necessary trips, such as going to work or school. Therefore, we controlled for the rate of work resumption, which represents the ratio of the cumulative active working population to the benchmark active working population. The cumulative value was calculated from February 1, 2020, and the baseline was taken from the active working population in December 2019. With the recovery of the urban economy and industry, the resumption rate gradually increased from zero to close to one. Moreover, we also controlled for the traffic count data in terms of daily subway passenger flow from January 1 to January 19, 2020 as it reflects a city's subway development level. The news that the disease can spread from person to person was officially announced on January 20, 2020. Prior to that date, passenger flows could be considered unaffected by the pandemic. Economic development is also associated with traffic volume. Therefore, we controlled for per capita GDP, as it represents the level of economy activity. The final control variable was derived from the Statistical Yearbook of Chinese Cities 2019.

Fig. 1 displays the evolution of the rate of work resumption for three treated cities. Hangzhou, Ningbo, and Xiamen implemented fare-free public transport policies when the process of work resumption reached 0.70, 0.79, and 0.81, respectively. Fig. 2 and Fig. 3 illustrate subway ridership in three treated cities and their donor pool. It can be seen that the predictors of Hangzhou, Ningbo, and Xiamen are generally at a medium level, which can be synthesized by other cities. Using the method described in Section 3.1, we constructed synthetic cities that mirrored the values of subway ridership in Hangzhou, Ningbo, and Xiamen. The pre-treatment RMSPE was minimized over four weeks before each policy implementation. The effect of these policies can then be estimated by comparing the observed subway ridership with its synthetic versions in the days after the policies came into effect. In addition, two principles were adopted when choosing the time period of

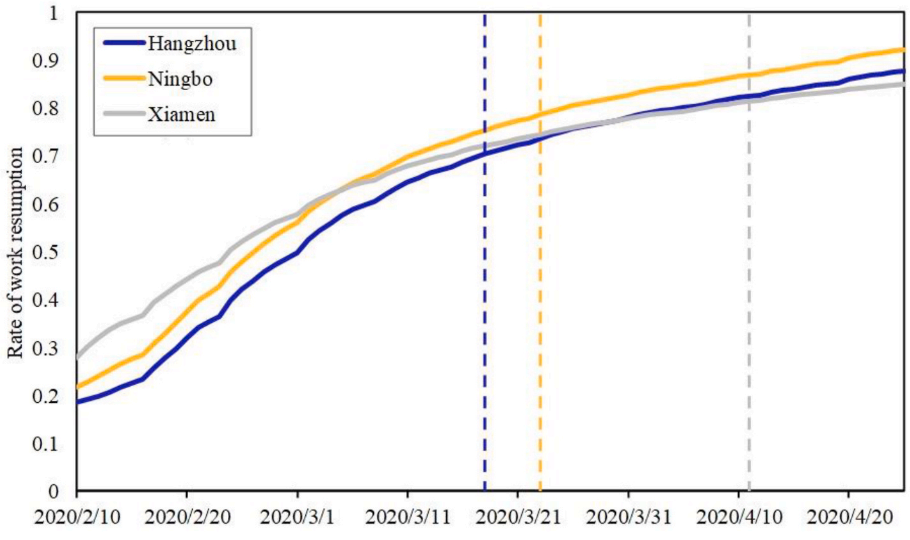


Fig. 1. The trend in the rate of work resumption in three treated cities.

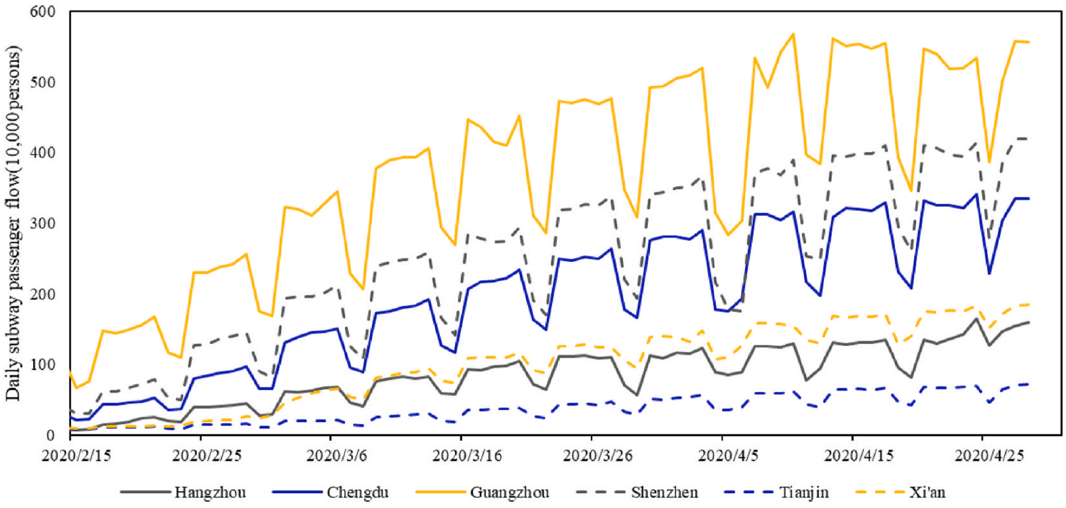


Fig. 2. Daily subway passenger flow in Hangzhou and its donor pool.

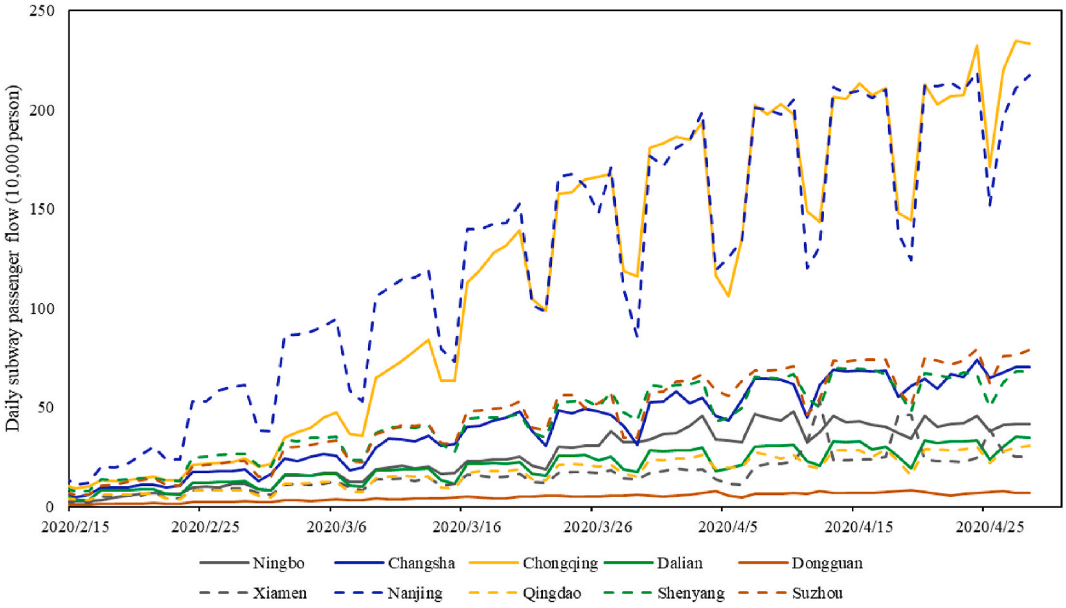


Fig. 3. Daily subway passenger flow in Ningbo and Xiamen and their donor pools.

the post-treatment effect. First, the effects of the fare-free public transport policies should be assessed before the end of policy implementation. Second, the donor pools and the treated cities should not encounter large changes. In regard to Hangzhou, the post-treatment effect was presented over the period from March 18 to March 30, 2020 because the PHFR policy was cancelled after March 31, 2020. As for Ningbo and Xiamen, the post-treatment effects were only displayed until April 25, 2020 because the effects of the fare-free public transport policy are likely to be contaminated by the operation of the new subway lines in their donor pool city (i.e., Shenyang) on April 29, 2020 and the holidays of May Day.

4. Results

This study used Stata 15.0 to run the SCM process. In this section, the results and analyses of Hangzhou, Ningbo, and Xiamen are presented. First, the weights of the donor pool for each treated city are displayed. Second, the counterfactual results of daily subway passenger flow without the intervention of the policies are reported. Then, the treatment effect of the policy implementation on daily subway passenger flow can be evaluated. Finally, the validity and robustness of the synthetic results are tested.

4.1. Baseline

To construct the counterfactual of the outcome for the treated city without the policy intervention, each city in the donor group generates a weight. The donor pool weights for synthetic Hangzhou, synthetic Ningbo, and synthetic Xiamen are shown in Table 2. An important aspect of the SCM is that the observed and synthetic outcome variables should be similar in the pre-treatment period. Section 3.1 proposes an RMSPE indicator to test the difference between the observed and synthetic outcome variables. Given that the RMSPE is influenced by the measurement and scale of the outcome variable, pre-treatment *t*-test was also used (Gius, 2019). In the pre-treatment period, the observed subway ridership should resemble the synthetic ones, thus the *t*-test statistics are supposed to be insignificant. Since the synthetic curve reproduces the counterfactual situation of the treated city, the impact of the introduction of the policy can be explained by the vertical gap between the observed and synthetic time trends during the post-treatment

Table 2
Donor pool weights.

City	Weight of synthetic Hangzhou	City	Weight of synthetic Ningbo	City	Weight of synthetic Xiamen
Chengdu	0.100	Changsha	–	Changsha	0.147
Guangzhou	–	Chongqing	–	Chongqing	–
Shenzhen	0.171	Dalian	0.157	Dalian	–
Tianjin	0.729	Dongguan	–	Dongguan	0.544
Xi'an	–	Nanjing	–	Nanjing	–
		Qingdao	0.655	Qingdao	0.310
		Shenyang	–	Shenyang	–
		Suzhou	0.188	Suzhou	–

Table 3
RMSPE for treated cities and t-tests for pre- and post-Treatment periods.

Treated city	RMSPE	Pre-treatment *t*-test statistics	Post-treatment *t*-test statistics
Hangzhou	2.769	−0.041	−1.589
Ningbo	1.153	0.270	12.071***
Xiamen	1.717	0.139	2.893*

Notes: *5% significance; **1% significance; ***0.1% significance.

period. Therefore, a *t*-test was also employed to determine the difference between the observed and synthetic subway ridership in the post-treatment period. The results of the RMSPE and t-tests are displayed in Table 3. In the pre-treatment period, there was no statistically significant difference between the observed and synthetic subway ridership for three treated cities. However, the effects of different fare-free public transport policies were somewhat inconsistent, according to t-tests in the post-treatment period.

There are three cities making up synthetic Hangzhou, of which Tianjin contributed the most, followed by Shenzhen and Chengdu (Table 2). Fig. 4 plots the observed and synthetic daily subway passenger flow for Hangzhou. The solid line represents the observed subway ridership of Hangzhou, while the dashed line represents the synthetic Hangzhou. The vertical dashed line represents the day when the policy came into effect. According to Fig. 4, the time trend of daily subway passenger flow for Hangzhou and synthetic Hangzhou before March 18, 2020, fits very well. Hence, the estimate of the effect of PHFR implementation is the gap between the solid line and the dashed line. After the vertical dashed line, daily subway passenger flow in the synthetic Hangzhou tracks the curve of that in Hangzhou. This finding is in line with the t-tests for Hangzhou in the post-treatment period, which shows that implementation of the PHFR policy did not have a significant impact on daily subway passenger flow.

As shown in Table 2, it can be concluded that daily subway passenger flow in Ningbo can be best reproduced by a combination of Qingdao, Suzhou, and Dalian. In the synthesis result of Ningbo (Fig. 5) the solid line and dashed line almost overlap before the vertical dashed line, which indicates that the synthetic Ningbo results are well. Immediately after the vertical dashed line, the synthetic Ningbo curve is obviously under the observed Ningbo curve. The positive difference between lines and the post-treatment t-tests seen in Table 3 suggest a promotion effect of MRMD and OPHFR policies. From March 23 to April 25, 2020, observed daily subway passenger flow in Ningbo was about 24% higher than that for synthetic Ningbo. Specifically, subway ridership increased by roughly 18% on weekdays and 40% on weekends. Table 4 shows the growth rate of passenger flow on different weekdays and weekends after the implementation of the policies. In general, the impact of the MRMD and OPHFR policies on the growth of passenger flow follows a trend that at first increases and then decreases. This result may be attributed to the fact that individuals' travel habits may have been less affected by the MRMD and OPHFR policies if they had regained confidence about the subway and as the process of work resumption approached completion. In any case, this study provides strong evidence that subway attraction can be actually enhanced by the implementation of MRMD and OPHFR policies.

Three cities were selected to construct the synthetic Xiamen, with Dongguan having the largest weight, followed by Qingdao and Changsha. Fig. 6 shows that synthetic Xiamen fairly reproduces the Xiamen trend in daily subway passenger flow until April 11, 2020, thereby suggesting that synthetic Xiamen provides a reasonable approximation of the subway ridership that would have been in Xiamen in the absence of the RDFD policy. On five rest days after the implementation of the RDFD policy, namely April 11, April 12, April 18, April 19, and April 25, subway passenger flow increased by approximately 94%, 172%, 135%, 152%, and 92%, respectively, compared with the counterfactual situation. As can be seen from Fig. 6 and from the post-treatment t-tests provided in Table 3, it can be concluded that the RDFD policy had remarkably increased the daily subway passenger flow on weekends.

4.2. Robustness

This study found that the fare-free public transport policies increased daily subway passenger flow in Ningbo and Xiamen; however, it is not clear whether the implementation effect is statistically significant. To test the validity and robustness of our results, we followed Abadie et al. (2010) by performing placebo tests. The basic idea of a placebo test is to apply the same analysis to the cities in the donor pool. That is to say, the

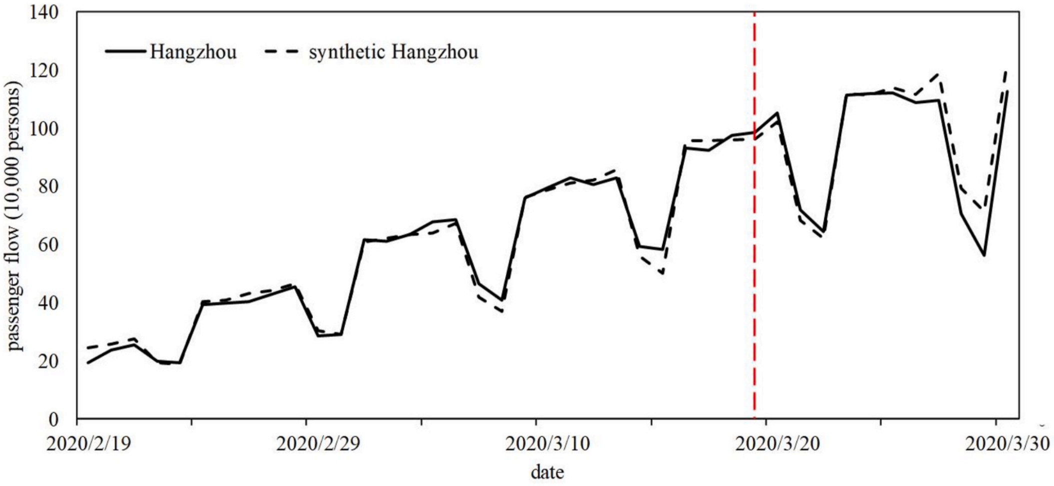


Fig. 4. Observed and synthetic trends of subway passenger flow in Hangzhou.

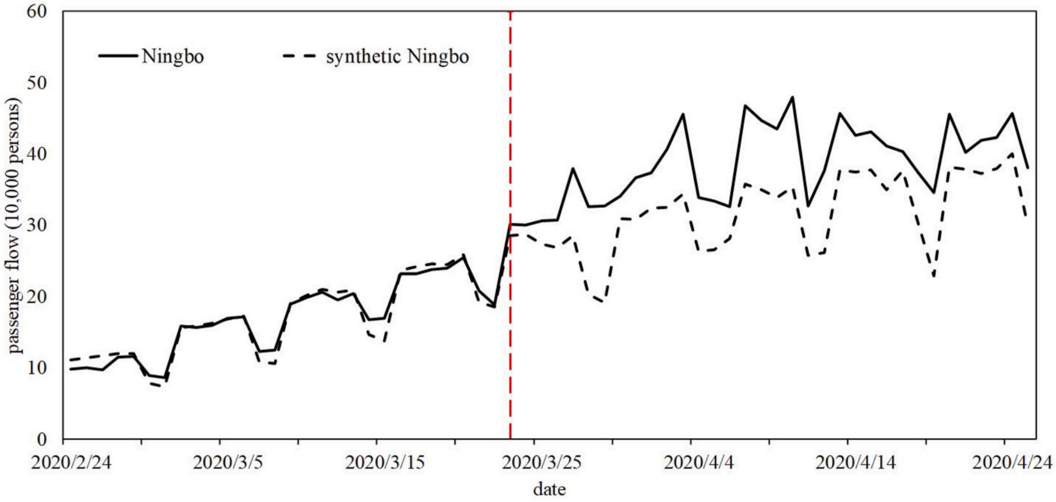


Fig. 5. Observed and synthetic trends of subway passenger flow in Ningbo.

Table 4

Increased rate of subway ridership in Ningbo.

Weeks after the policy implementation	First week	Second week	Third week	Fourth week	Fifth week	Total
Weekday	13.9%	20.4%	27.7%	14.7%	12.8%	17.9%
Weekend	66.1%	27.2%	35.4%	37.4%	27.3%	40.0%
Weekday + weekend	28.8%	22.3%	29.9%	21.2%	15.2%	23.7%

fare-free public transport policy is applied to each city in the donor pool and the effect of the policy implementation is also estimated using SCM. To compare the gap for the treated city with the gaps obtained from the placebo tests, the ratio between the "post-treatment RMSPE" and the "pre-treatment RMSPE" is calculated. If this ratio of the treated city is unusually higher than that of the control cities, it is likely that the estimated treatment effect is attributable to fare-free public transport policies. The distributions of the ratios are displayed in Fig. 7. The ratio for Ningbo is the largest of the placebo tests, and Xiamen's ratio clearly stands out among the placebo tests, which indicates that the effect of policies on subway ridership is robust. Nevertheless, our results should be interpreted with caution because of the number of control cities in this study was relative small.

5. Discussion

The purpose of fare-free public transport policy in different cities is to switch the personal motorized travel to public transport usage after the lockdowns eased. The results of this research prove that MRMD and OPHFR policies in Ningbo increased subway ridership by about 24% in the first month, and the RDFR policy in Xiamen increased subway ridership 2.3 times over five rest days. In most cities, the majority of the increased ridership brought by the free public transport is among those who would rather walk, cycle, or not travel at all (Fearnley, 2013). In addition to these people, the MRMD policy also attracted people who would have used other public transport (e.g., buses), because this policy only applied to subway usage. There is evidence that the fare elimination effect has been found to be significant for shopping motive (Cools et al., 2016). Given that unnecessary trips and leisure trips generally take place in off-peak hours on weekdays, weekends, and holidays, the OPHFR and RDFR policies are likely to stimulate subway use for these types of trips. Although this present study confirmed the merits of MRMD, OPHFR, and RDRF policy as a means to increase public transport use for the post-COVID-19 era, it is worthwhile to further look at the impact of temporary fare-free public transport policies on helping subway ridership rebound to historical levels. To this end, intensity of subway ridership (ISR), which is the ratio of daily subway ridership to subway operating mileage in a city, is used to reflect the congestion

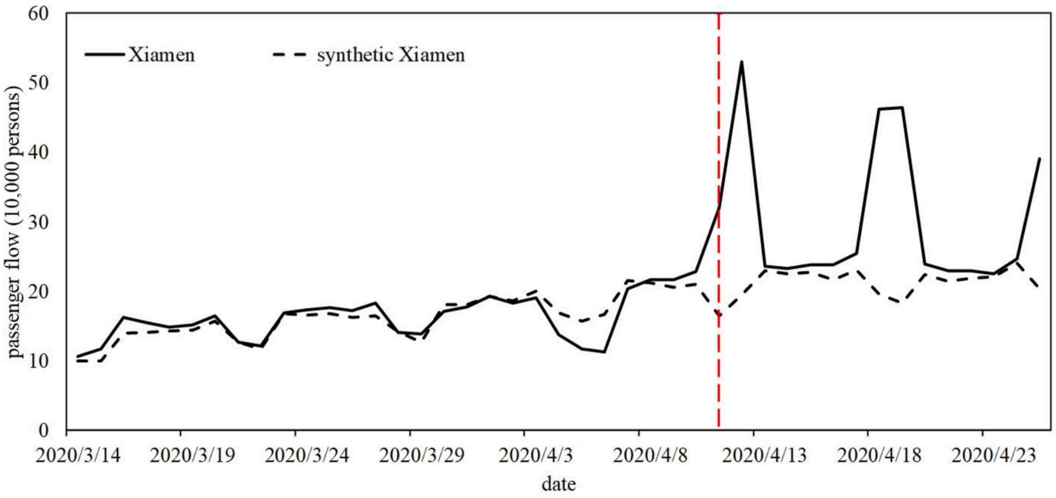
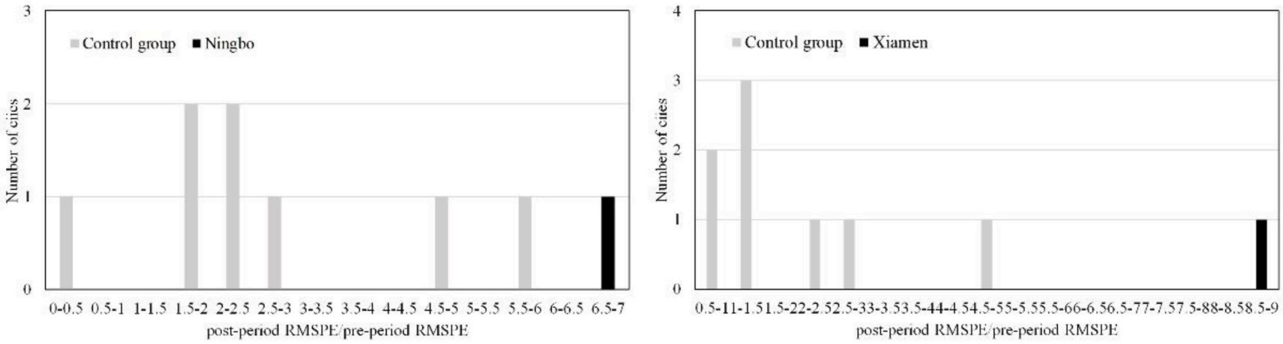


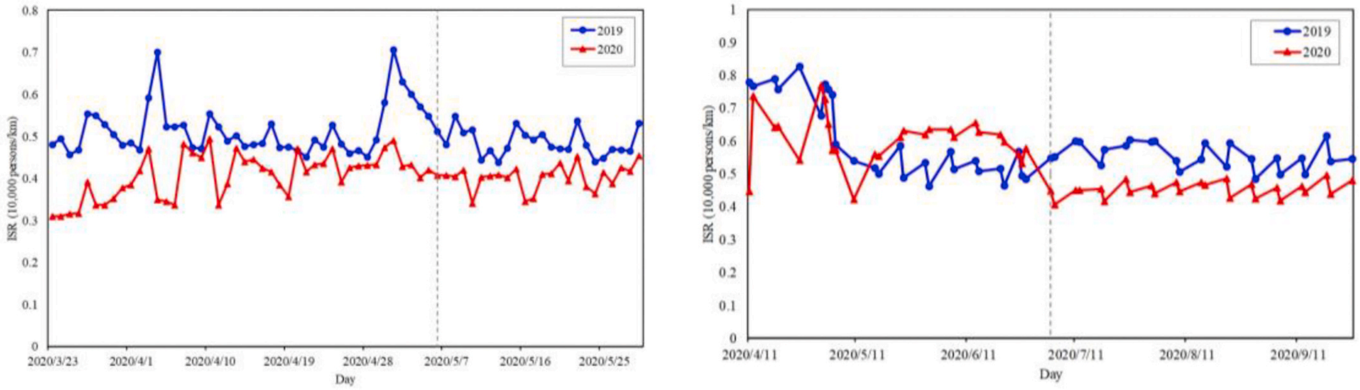
Fig. 6. Observed and synthetic trends of subway passenger flow in Xiamen.



(a) Ningbo

(b) Xiamen

Fig. 7. Placebo test for Ningbo and Xiamen.



(a) Ningbo

(b) Xiamen (weekends)

Fig. 8. ISR comparison between the post-pandemic stage and the correspond day in last year.

status of the subway network in a city and eliminate the effect of the operation of new subway lines. The historical day that corresponds to the day in the post-pandemic stage is found from the dates in the last year. To be specific, the holidays (e.g., May Day and Chinese Memorial Day) should be matched firstly; then, weekdays and weekends are matched according to the number of days around each holiday and the day of week. Fig. 8 displays the trend of ISRs from the beginning of fare-free public transport policies in Ningbo and Xiamen, respectively, and the dashed vertical line represents the end of the policy implementation. As Ningbo opened new subway line in May 30, 2020, Fig. 8 (a) presents the ISR comparison between the day in the post-pandemic stage that ranges from March 23, 2020 to May 29, 2020 and the corresponding historical day that ranges from March 25, 2019 to May 31, 2019. It can be seen that before and after the implementation of the MRMD and OPHFR policies, the ISR in post-COVID-19 era did not catch up with the level of the same period last year. In regard to Xiamen, Fig. 8 (b) shows the ISR comparison between the weekends in the post-pandemic stage that ranges from April 11, 2020 to September 30, 2020 and the corresponding historical day that ranges from April 13, 2019 to September 30, 2019. During the implementation of the RDFD policy, the weekend ISR in the post-pandemic stage rebounded to and sometimes exceeded the level of the same period last year. However, once the free policy was cancelled, the weekend ISR was still lower than that in the same period last year. From the policy perspective, in order not to waste the funds, the multi-pronged approaches should ensue after the end of the temporary fare-free public transport policies. For instance, controlling the total number of automobiles when using car consumption to hedge against the economic impact of the pandemic is an another way to reduce car use. From a psychological point of view, regaining the confidence and forming a positive attitude toward subway were found to be the crucial determinants in the stage of travel behavior change (Friman et al., 2019). Thus, possible methods include examining health identification cards, adding mask purchase options to subway vending machines, regulating the passengers as well as the transport operators to follow the behavioral rules in subway, and displaying the completion of cleaning and hygiene activities.

The implementation of a PHFR policy has no obvious effect on subway ridership. Regular and routine trips (e.g., commuting trips) generally take place in peak hours. The difficulty of "breaking the routine" has been reported in published research (Abou-Zeid and Ben-Akiva, 2012; Thøgersen and Møller, 2008). Individuals have a strong tendency to repeat past decisions (Cools et al., 2016). That is, individuals are less likely to reconsider how to go to work on a daily basis once they find a suitable way to commute. In addition, it is noteworthy that the PHFR policy in Hangzhou lasted only 14 days. From a short-term perspective, the fare-free public transport policy showed a weak effect on modal choice, while a strong motivation to change may play a role over time (Friman et al., 2019). Therefore, it is suggested that a PHFR policy should be implemented for a relative long time to see whether the long-term effects can change commuters' travel behavior during peak hours. The different effect of fare-free public transport policy in the three treated cities indicates that whether these policies will lead to a substantial increase in public ridership depends largely on the context. First, the economic approach to entice people to use public transport during peak hours are questionable because it means that social distancing behavior that people have developed during the pandemic may be broken, thus causing people to have feelings of discomfort and dangerous. Second, encouraging people to make trips during off-peak hours could be a win-win situation. On the one hand, it contributes to the adjustment of the persons' activity plans and travel behaviors; on the other hand, it mitigates the economy losses and avoids the social isolation by generating increased demand for goods and services in other sectors. Third, other countries across the world should apply the fare-free public transport policy according to local conditions and shouldn't apply it dogmatically. As Xiamen is a famous tourist city in China, the RDFD policy are expected to attract local citizens and visitors to go sightseeing on weekends and holidays. Authorities in other cities should also formulate the rules for the fare-free public transport policy according to the characteristics of the city.

Rebound effects of fare-free policies should also be considered. When the public responds to the call of the fare-free public transport policies, a large increased subway ridership could lead to a higher tax burden. Since estimating the cost of an MRMD policy using short-term data is difficult, and an OPHFR policy applies to a specific service time, this study only gives a rough financial estimate for Xiamen. The per capita subway fare in Xiamen is assumed to be 3 yuan, which indicates that the average subway travel distance is between 4 km and 8 km. As a result, Xiamen has spent approximately 34 million yuan for its RDFR policy. This expenditure accounts for about 25% of the 2020 public transport operation subsidy budget of Xiamen's transport department, which is reportedly about 134 million yuan (Xiamen Transport Bureau, 2020). As a matter of fact, the per capita GDPs of Xiamen and Ningbo are 132,000 and 118,000 yuan, respectively, which is about twice of the average China's per capita GDP. Even in such relatively developed cities, the fare-free public transport policies were lifted three months after it began. Therefore, if a city intends to implement a fare-free public transport policy, it needs to ensure an abundant and stable funding stream to support the reform. The potential funding stream may come from local government, induced consumption of goods and services, and special treasury bonds aimed at mitigating the economic and social impact of COVID-19.

In addition, it can be seen that when the free policy is implemented, subway passenger flow is likely to recover or exceed the level of the same period last year. Therefore, if the supply does not follow the demand, a decline in the service quality could be observed. On the one hand, this is unfair to people who rely on public transport for travel. On the other hand, if the service quality cannot be guaranteed, then when the fare-free policy ends, it is likely to cause a sharp drop in subway ridership. Therefore, there is an urgent need for collateral measures to improve the efficiency and safety of riding public transport. A combination of measures, such as controlling the maximum number of passengers, increasing frequency, alternating stops, and redefining the right of way, can help to ensure the level of services. The fare-free public transport policy may be a temporary stimulus as it imposes high burden on the local government and transport operator. As the COVID-19 makes people more likely to use walking and cycling (De Vos, 2020; Teixeira and Lopes, 2020), integrating the active transportation with subway are expected to play an important role in increasing the accessibility and solving the first-/last-mile problem of public transport. Hence, establishing mobility hub near subway station, adjusting the spatial and temporal distribution of the shared bikes, and planning sidewalks and bike lanes could be used as the supplementary measures, aimed at increasing the attraction of public transport and adapting to the new normal brought by COVID-19.

6. Conclusion

Three Chinese cities have announced fare-free public transport policies following a global slump in demand in subway usage because of the coronavirus crisis. The synthetic control approach has provided estimates of the effects of three different types fare-free public transport policies on daily subway passenger flow. When it comes to the growth rate of subway ridership, MRMD and OPHFR policies in Ningbo and RDFR policy in Xiamen have lived up to the governments' expectations. The MRMD and OPHFR policies increased subway ridership by about 24% in the first month, and the RDFR policy increased the subway ridership by a factor of 2–3 on weekends. However, the PHFR policy in Hangzhou showed little impact on increasing subway ridership. A possible reason for the insignificant effect of the PHFR policy could be that fare elimination may be more powerful for non-habitual and leisure trips than for commuting trips. Moreover, a suitable fare-free public transport policy is a feasible way to help the subway increase ridership in the post-COVID-19 era, but it should also be combined with other measures to restore the ridership to historical levels. The results of this study can be used as a reference for other cities to formulate appropriate fare-free public transport policies and complement measure to increase the subway ridership.

A number of notable limitations still exist in this study. First, the limited number of control cities in the donor pool decreases the robustness of the results. As a second drawback, this study does not separate the generation effect and substitution effect of fare-free public transport policies. Hence, further efforts should be undertaken to investigate the relationships between motorized travel, active transportation, and public transport. Finally, we merely used the before-and-after comparison method to observe the ISR changes between the post-pandemic stage with the corresponding historical day in last year. Future studies should consider adopting an objective and theoretically grounded approach to assess the effect of fare-free public transport from a long-term perspective.

Author statement

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Declaration of competing interest

None.

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