The regression control method-based influential analysis on the transit metropolis policy in China

Jiaxin Yuan*

School of Economics and Management, Nanjing University of Science and Technology, Nanjing, China

*Corresponding author: 924297854@qq.com

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Abstract: The policy of 'Transit Metropolis' has been implemented in China almost ten years, which aims to alleviateurban traffic congestion. In order to evaluate the performance of this policy, this paper constructs an indicator using the HCW method (Hsiao, Ching and Wan), which counts passenger volume per capita. Furtherly, three measurement methods including 'permutation test method', 'time placebo test' and 'leave-one-out method' are adopted to test the robustness of the proposed indicator. The results indicate that this policy has a positive impact on the pilot cities. However, only three cities of Beijing, Tianjin and Nanchang show significant policy effects. The resuts show that the dividend of the current demonstration project policy has not been fully released, and the policies of the free trade pilot zones in various regions urgently need to be optimized furtherly.

1. Introduction

Traffic congestion has become an important factor restricting the rapid development of the urban economy. The main impacts are as follows[1]: Firstly, traffic congestion increases the travel time and cost consumption of residents; secondly, traffic congestion increases the probability of traffic accidents; thirdly, traffic congestion leads to environmental pollution, and frequent acceleration and deceleration of vehicles will increase exhaust emission, resulting in air pollution. In order to better solve the problem of urban traffic congestion, the Ministry of transport began to implement the 'Transit Metropolis' construction demonstration project in 2012, and selected some cities for implementation, so as to promote the further development of urban public transport.

There have been different perspectives on how to achieve the goal of the demonstration project. Different cities adopt different methods, such as building more roads, increasing public transport vehicles, and increasing bus lines. How will different implementations of policy affect the relief of urban congestion? This problem has attracted the attentions of various social groups. At present, the scope of demonstration projects of transit metropolis is gradually expanding. The pilot cities for demonstration projects announced in 2012 and 2013 reflect different ideas for solving traffic congestion and are of great significance to the construction of transit cities. Therefore, this study uses the HCW method to conduct an in-depth and systematic quantitative evaluation of the policy effects of demonstration projects, so as to provide a scientific basis for establishing transit metropolis and alleviating traffic congestion.

2. Literature review

The type of transit metropolis changes with the specific situation of the city. Different cities develop different characteristics of transit metropolis according to their scale, environment, and functional structure. The strategic development direction and policy focus of different cities are different, and the content of policy evaluation is diversified.

Since this policy is implemented in China, and a lot of Chinese researchers have studied this policy, this study has reviewed this works in Chinese and summarized in English, in order to better demonstrate the existing works on this topic as well as provide a comprehensive view from Chinese researchers.

The study of Francois et al.[2]used an integrated microscopic traffic simulation model to analyze and evaluate the potential benefits of implementing a bus signal priority strategy along the Colombian Pike corridor. Khaled et al.[3] evaluated the implementation effect of public transport signal priority (TSP) measures in the VISSIM multi-modal micro-simulation environment to test the performance of the transportation network. Taefi et al.[4] conducted a multi-criteria analysis of Germany's policy measures to support pure electric freight vehicles, providing a scientific basis for policy formulation. Ma, Fan, Feng[5] used panel co-integration model to quantitatively analyze the long-term and short-term effects of China's energy vehicle sales and driving policies. Regarding China’s Transit Metropolis policy in 2012, Ji, Zhang and Chen[6] optimized the objectivity and accuracy of the public transportation priority development evaluation model through the matter-element extension model and the improved entropy method for calculating interval values. Liu et al. [7] proposed a four-in-one evaluation framework of ‘goal-action-diagnosis-technology’, taking Wuhan as an example, based on scenario evaluation, and pointed out the key to achieving high-quality urban development and transformation. An et al.[8] proposed the use of six evaluation criteria to determine whether the urban development model conforms to the concept of priority development of public transportation, and proposed optimization suggestions for the evaluation index system of the transit city. Xu[9] conducted an evaluation study on the public transportation financial subsidy system and established a new evaluation index system based on the BSC concept and AHP method to provide support for the scientific evaluation of the effect of urban public transport subsidy policies. The study of Li et al[10] evaluated and compared the development of public transportation systems towards Transit Metropolis status in different cities in China with an enhanced fuzzy analytical hierarchy process (AHP) model.

In general, the focus of research on the policy evaluation of China's public transit metropolis is to establish an evaluation index system, which is subjective. Panel data is rarely used to analyze and evaluate the effect of the implementation of public transit metropolitan policies, so it cannot objectively reflect the effect of public transit city demonstration projects.

The quantitative analysis of policy evaluation mostly adopts the difference in difference model. The difference in difference model can compare the changes of related variables after the implementation of the policies in the pilot cities and the related variables that are not affected by the policies. The difference between the two reflects the impact of the policies on the pilot cities. Zhou et al.[11] evaluated the impact of the host country’s transportation facilities on overseas mergers and acquisitions under the ‘Belt and Road’ initiative through the difference in difference model. Fan et al.[12] verified the impact of the opening of high-speed rail on the intensity of industrial pollution emissions by constructing a difference in difference model. Yu et al.[13] used the difference in difference model and propensity score matching- difference in difference model to assess the impact of the opening of high-speed rail on the urban-rural income gap.

However, the difference in difference model has the following two problems: (1) The selection of the control group is subjective and arbitrary, and is not convincing; (2) the policy is endogenous, and there are systematic differences between the pilot cities and other cities, and this difference happens to be the reason why the city became a pilot city[14]. Therefore, the results obtained by using difference in difference models directly will be biased.

In view of the shortcomings of difference in difference model, the new development ‘natural experiment method’, the HCW method, and the synthetic control method (SCM), can be used to evaluate the policy. This type of method does not require the selection of the experimental group and the control group to be random, nor does it require the two to have a common development trend. HCW method and synthetic control method have gradually become effective tools for policy effect analysis. For example, Huang et al.[15] used synthetic control methods to simulate consumption in Ningbo and Jiaxing in the absence of the opening of the bridge, and analyzed the retail sales before and after the opening of the bridge. Xiao[16] used the synthetic control method to compare and analyze the effects of the subway construction and traffic restriction policies, and the results showed that the subway construction is more conducive to alleviating air quality. Li et al.[17] comprehensively assessed the impact of the purchase restriction policy on urban housing prices through the HCW method. Chen et al.[18] used the HCW method to study the impact of the introduction of China's margin trading system on the volatility of the stock market, and the results showed that the introduction of the margin trading system effectively reduced the volatility of individual stocks. The HCW method and SCM method have gradually been widely used in the field of policy evaluation.

The policy evaluation method adopted in this paper is the HCW method proposed by Hsiao et al.[19]. Compared with the difference in difference model, it has the following advantages[20]: (1) HCW believes that the common factors in the system have a certain degree of linkage or correlation in cross-section, so the variables of the control group can be used as the basis for constructing ‘counterfactuals’. Through linear regression improvements, the weights of individuals in the control group are more economically meaningful and unique. (2) HCW can overcome the difficulties of unclear causality, complicated theoretical modeling, missing variables, and insufficient time series data in macro policy evaluation, and reduce the interference of variable selection and estimation methods on the robustness of empirical results. Compared with the synthetic control method, HCW has the following advantages[21]: (1) The HCW method only needs the result variable data of all samples, and the synthetic control method requires the sample result variable data and predictive covariate data. (2) The HCW method allows the weight of the control group to be negative, and the weighted sum is not necessarily 1, but the synthetic control method requires the weight of the control group to be positive and the sum is 1. At the same time, this study proves that the HCW method is also practical in this field.

3. HCW-based evaluation method

3.1 Sample source

In 2012, the Ministry of Transport announced the list of the first batch of pilot cities for transit metropolis, and in 2013 the second batch of cities were announced. Finally, there are 37 cities in total. This paper regards the demonstration project as a natural experiment carried out on the pilot cities, and cities affected by the policy are selected as the treated group, and cities not selected as the pilot are selected as the control group, as shown in Table 1. The studied data are collected from the ‘China City Statistical Yearbook’ from the year of 2003 to 2018.

Table 1. Cities of treated group and control group

<table>
<tr><th colspan="2">Group</th><th>Cities</th></tr>
<tr><td rowspan="2">Treated group</td><td>The first batch</td><td>Beijing, Shijiazhuang, Taiyuan, Dalian, Harbin, Nanjing, Jinan, Zhengzhou, Wuhan, Changsha, Shenzhen, Chongqing, Kunming, Xi’an, Urumqi</td></tr>
<tr><td>The second batch</td><td>Tianjin, Hohhot, Shenyang, Changchun, Shanghai, Ningbo, Hefei, Fuzhou, Nanchang, Qingdao, Guangzhou, Haikou, Guiyang, Lanzhou, Xining, Yinchuan, Baoding, Suzhou, Hangzhou, Xinxiang, Zhuzhou, Liuzhou</td></tr>
<tr><td colspan="2">Control group</td><td>Xiamen, Nanning, Chengdu, Tangshan, Qinhuangdao, Baotou, Dandong, Jinzhou, Jilin, Mudanjiang, Wuxi, Yangzhou, Xuzhou, Wenzhou, Jinhua, Bengbu, Anqing, Quanzhou, Jiujiang, Ganzhou, Yantai, Jining, Luoyang, Pingdingshan, Yichang, Xiangyang, Yueyang, Changde, Huizhou, Zhanjiang, Shaoguan, Guilin, Beihai, Sanya, Luzhou, Nanchong, Zunyi</td></tr>
</table>

3.2 Assessment method

As described in the literature, HCM method seems to be a good fit for this study. Taking the case in this study as an example, an application of HCM method is as follows:

Assuming that the growth of passenger traffic volume in J + 1 cities can be observed, only the first region (pilot city) is affected by the transit urban policy in the period of T_0+1， …,T, which is recorded as the processing group, and the remaining J cities constitute the control group, and these cities are not affected by the policy.

Suppose that at time t, the urban passenger transport volume of city j is Y_{jt}. Y_{jt}^0 and Y_{jt}^1 represent the passenger traffic volume of city j at time t under treatment and in the absence of interference. Y_{jt}, the passenger volume of city j at time t can be written as:

$$Y_{jt} = d_{jt} Y_{jt}^{1} + (1 - d_{jt}) Y_{jt}^{0} \quad (1)$$

d_{jt} is a dummy variable. If city j is affected by the policy at time t, the value is 1, otherwise, the value is 0. Only the first city is affected by the policy, so the following equation can be obtained:

$$d_{jt} = \begin{cases} 1 & \text{if j=1 and t>}T_0 \\ 0 & \text{other} \end{cases} \quad (2)$$

Therefore, the impact of the policy on the pilot cities can be expressed as:

$$\alpha_{1t} = Y_{1t}^{1} - Y_{1t}^{0} \quad (3)$$

For $t > T_0$, Y_{1t}^{0} cannot be observed, and α_{1t} cannot be calculated directly. The panel data method proposed by Hsiao et al.[19] predicts Y_{1t}^{0} for $t > T_0$ by using the dependence between the cross-sectional units of the control group and the treatment group, thereby estimating the impact of the policy α_{1t}. Then use R^2 ((or likelihood) to select the best OLS estimator of Y_{1t}^{0} from j cities in J control groups, using $M(j)^*$ to represent j=1,…,J; finally, according to the model selection criteria, select $M(m)^*$ from $M(1)^*$, …, $M(J)^*$.

This strategy is based on the following basic model. Hsiao et al.[19] assume that Y_{jt}^{0} is composed of the following dynamic factor model:

$$Y_{jt}^{0} = y_j + f_t b_j + \varepsilon_{it} \quad (4)$$

y_j represents the individual effect of the city, f_t is a (1×K) vector that represents unobserved common factors that change over time, b_j represents a (K×1) vector that changes with the change of j, and K is the number of common factors, ε_{it} is the time-varying characteristic of individual j.

According to the model proposed by Hsiao et al. (2012) to predict Y_{1t}^{0}, use the city $Y_{-1t} = (Y_{2t}, \dots, Y_{(J+1)\,t})$ that is not affected by the policy in the control group to predict Y_{1t}^{0}:

$$Y_{1t}^{0} = \alpha + \beta Y_{-1t} + \varepsilon_{1t} \quad (5)$$

This article uses the R package ‘pampe’ provided by Vega-Bayo[22] to perform the HCW method.

3.3 Variable selection

According to literature review, the main factor causing urban congestion in China[23] is that the growth rate of the current road network cannot meet the people's travel demand, and the growing trend of car ownership has not slowed down. The increase in the number of private cars is due to people’s pursuit of high-quality travel. Therefore, when the public transportation system of pilot cities can provide higher-quality public transportation services, people will choose public transportation as a mode of travel, reducing the use of cars, and thus alleviate the problem of urban congestion.

According to the transit metropolis assessment index system published by the Ministry of Transport, the first consideration is the travel sharing rate, followed by the bus and tram line network ratio. The purpose is to increase the chances of residents choosing public transport services by improving public transport operation and service quality. The increase in the share of public transport travel is reflected in the increase in passenger volume per capita. Therefore, this paper chooses the number of passenger volume per capita in the city as the explained variable, the number of passenger volume per capita = Annual bus and trolley bus passenger volume/year-end total urban population.

4. Policy effect analysis

4.1 Counterfactual analysis of policy effect

According to the HCW method, this part calculates the optimal control group and corresponding weights of the first batch of pilot cities and the second batch of pilot cities in passenger volume per capita. Some results are shown in Table 1. According to the optimal control group and weights in

Table 1, the ‘counterfactual value’ of the passenger volume per capita index of the treated group is calculated, and the effect of the indicator policy in each treated area is evaluated and comparatively analyzed according to the ‘counterfactual value’, details as follows:

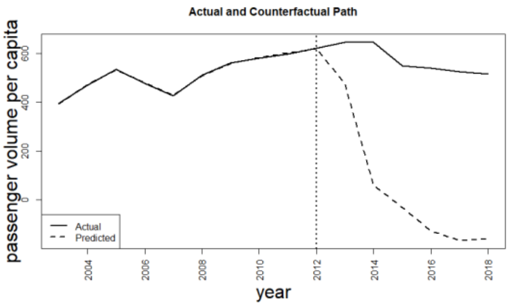
Table 2. Optimal control group and weight

Control group	passenger volume per capita							
	Beijing	Chongqing	Tianjin	Ningbo	Hefei	Nanchang	Haikou	Xinxiang
Xiamen								0.114
Nanning								-0.244
Chengdu								
Tangshan	-2.137							
Qinhuangdao			0.847					
Baotou	-1.026			0.289				
Dandong								
Jinzhou								
Jilin				1.8				
Mudanjiang		0.321			-0.453		0.593	
Wuxi								
Yangzhou								
Xuzhou								
Wenzhou			0.657		0.894			
Jinhua			-0.783		-0.685			
Bengbu		0.183						
Anqing						2.002		-1.439
Quanzhou		0.109						
Jiujiang		0.338						
Ganzhou			0.406			-0.391		
Yantai					-1.778			0.907
Jining						0.526		
Luoyang								
Pingdingshan								
Yichang							-1.326	
Xiangyang	-4.464						2.859	
Yueyang		0.065		0.146				
Changde								
Huizhou			0.090					
Zhanjiang			0.105					
Shaoguan		-0.385						
Guilin	3.804			-0.194	2.184			
North Sea						1.058	-2.483	
Sanya								
Luzhou		1.383				-0.150		
Nanchong				-0.305			0.922	
Zunyi								
Intercept	43.181	-46.425	-102.400	7.096	-125.481	73.189	37.267	56.438
Adj.R^2	0.998	0.9946	1	0.999	0.999	1	0.999	0.999

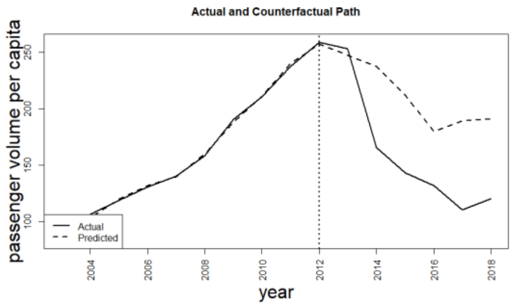
Five cities in the treated group are selected to show the ‘actual value’ trend line of passenger volume per capita before and after the establishment of the transit metropolis and the ‘counterfactual value’ trend line obtained based on the HCW method. Among them, the position of the vertical line represents the starting year of the demonstration project, and the distance between the ‘actual value’ line and the ‘counterfactual value’ line on the left side of the vertical line reflects the fit of the optimal control group to the treated group. If the distance between the two is smaller, the fitting effect is better. The distance between the ‘actual value’ line and the ‘counterfactual value’ line on the right side of the vertical line reflects the policy effect α_t of the demonstration project. If the distance between the two is greater, the treated group may be subject to greater policy effects. Select Beijing, Shijiazhuang, Harbin, Nanjing, and Guangzhou from the treated group to make a trend line graph, as shown in Figure 1. Table 2 reports the average policy effect value of the passenger volume per capita of Beijing, Shijiazhuang, Harbin, Nanjing, and Guangzhou during the observation period.

Table 3. Average policy effect value of passenger volume per capita of experimental group

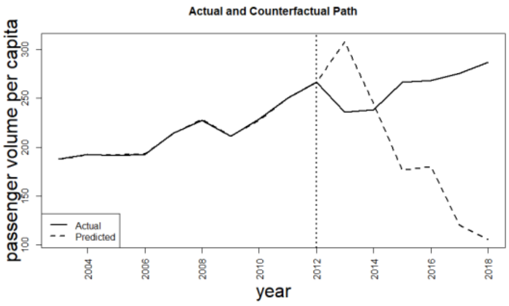
	Beijing	Shijiazhuang	Harbin	Nanjing	Guangzhou
α_t	561.9971	-55.5795	41.44209	72.55192	-28.1916



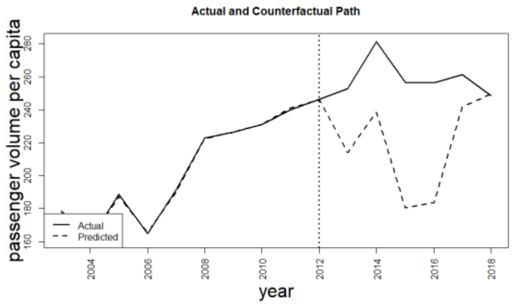
(a)Beijing



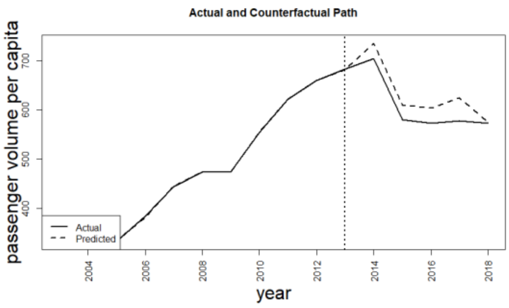
(b)Shijiazhuang



(c)Nanjing



(d) Harbin



(e)Guangzhou

——Actual ----Counterfactual

Figure 1 Trend line of ‘actual value’ and ‘counterfactual value’ of passenger volume per capita

It can be seen from Figure 1 that on the left side of the vertical line, the ‘counterfactual value’ lines of each treated group all made a good fit to the important inflection point of the ‘actual value’ line, and the two curves tend to overlap, which shows that Evaluation based on counterfactual values can get more reliable results. On the right side of the vertical line, it can be found that the policy effects of each treated area have shown different forms. Specifically, from the perspective of Beijing, the demonstration project has played a strong role in promoting the number of passenger volume per capita since 2013, making its actual value significantly higher than its counterfactual value. During the observation period, Beijing's average policy effect reached 561.9971, which is the largest among the six treated areas, which shows that the demonstration project can greatly promote Beijing's passenger volume per capita. The actual value of Shijiazhuang was higher than its counterfactual value in the first period, but in the rest periods, the actual value of Shijiazhuang was lower than its counterfactual value. The average policy effect was -55.5795. From the perspective of Nanjing, the policy effect of Nanjing is the opposite of Shijiazhuang. Except in 2013 and 2014, the actual value of Nanjing is significantly higher than its counterfactual value. During the observation period, the average policy effect of Nanjing reached 72.55192. From the perspective of Harbin, the actual value of Harbin is slightly lower than its counterfactual value in the last period. In the rest of the time, the actual value of Harbin is greater than its counterfactual value. In general, the demonstration city has played a role in promoting the passenger volume per capita in Harbin. For Guangzhou, the difference between the actual value and the counterfactual value is small, and it is very close in the last phase, which indicates that the demonstration project has little impact on the passenger volume per capita in Guangzhou.

4.2 Effectiveness analysis of policy effect

In the process of constructing demonstration projects in the treated group cities, the control group cities will also formulate policies to promote the sharing rate of public transportation and alleviate traffic congestion. Then, compared with the urban development that has not been selected as the demonstration project, does the demonstration project bring more significant effects and influence on the cities in the treated group? This point is not clear in the counterfactual analysis above. Since the non-parametric estimation results obtained by using the HCW method cannot be tested for significance by using traditional large-sample statistical inference techniques. Therefore, using Jian Wu and Wei Xie[21] permutation test method, the experimental group's policy effect estimation results are tested whether they reach a significant and effective level. Specific steps are as follows:

First, assume that all cities that are unselected as demonstration projects have implemented the transit metropolis policy at the same time as the treated group, and then use the HCW method to find the optimal control group and weight for each control group in the remaining J-1 control group.

Second, calculate the $\mathrm{RMSPE}_{\mathrm{j}}^{\mathrm{Pre}}$ statistics of the passenger volume per capita indicators in all the treated groups and control groups, as follows:

$$\mathrm{RMSPE}_{\mathrm{j}}^{\mathrm{Pre}} = [\frac{1}{\mathrm{T_0}}\sum_{t=1}^{\mathrm{T_0}}(\mathrm{Y}_{\mathrm{j}t}^{1} - \mathrm{Y}_{\mathrm{j}t}^{0})^2]^{\frac{1}{2}} \tag{6}$$

In formula (6), the $\mathrm{RMSPE}_{\mathrm{j}}^{\mathrm{Pre}}$ value reflects the overall fit of the j region in the optimal control group for the passenger volume per capita, $\mathrm{Y}_{\mathrm{j}t}^{1} - \mathrm{Y}_{\mathrm{j}t}^{0}$ is the 'fitting error value' of the passenger volume per capita in the j region in the time t before the demonstration project, the value of $\mathrm{Y}_{\mathrm{j}t}^{1} - \mathrm{Y}_{\mathrm{j}t}^{0}$ is smaller, the $\mathrm{RMSPE}_{\mathrm{j}}^{\mathrm{Pre}}$ value is smaller, indicating that the optimal control group has a better fitting effect on the passenger volume per capita during the $\mathrm{T_0}$ period.

Third, calculate the $\mathrm{RMSPE}_{\mathrm{j}}^{\mathrm{Post}}$ statistics of passenger volume per capita in all the treated groups and control groups, as follows:

$$\mathrm{RMSPE}_{\mathrm{j}}^{\mathrm{Post}} = [\frac{1}{\mathrm{T}-\mathrm{T_0}}\sum_{t=\mathrm{T_0}+1}^{\mathrm{T}}(\mathrm{Y}_{\mathrm{j}t}^{1} - \mathrm{Y}_{\mathrm{j}t}^{0})^2]^{\frac{1}{2}} \tag{7}$$

In formula (7), if the j region belongs to the treated group, the $\mathrm{RMSPE}_{\mathrm{j}}^{\mathrm{Post}}$ value reflects the overall impact of the demonstration project on the passenger volume per capita. If the data of the j region is in the control group, the $\mathrm{RMSPE}_{\mathrm{j}}^{\mathrm{Post}}$ value reflects the overall impact of the implementation of the 'transit metropolis' policy on the passenger volume per capita. $\mathrm{Y}_{\mathrm{j}t}^{1} - \mathrm{Y}_{\mathrm{j}t}^{0}$ is the 'prediction error value' of the passenger volume per capita in the j region in the year t after the demonstration project was established. The larger the value, the larger the $\mathrm{RMSPE}_{\mathrm{j}}^{\mathrm{Post}}$ value, indicating that the policy implemented in the j region during the $T_0 - T$ period has a greater impact on the passenger volume per capita.

Fourth, calculate the $RMSPE_j^{Post/Pre}$ statistics of the passenger volume per capita in all sample areas, as follows:

$$RMSPE_j^{Post/Pre} = \frac{RMSPE_j^{Post}}{RMSPE_j^{Pre}} \tag{8}$$

In formula (8), the value of $RMSPE_j^{Post/Pre}$ reflects the overall policy effect of passenger volume per capita in the j region. When the value of $RMSPE_j^{Pre}$ is smaller, the value of $RMSPE_j^{Post}$ is larger, indicating that the policy effect obtained by the j region in passenger volume per capita is larger.

Fifth, compare the $RMSPE_j^{Post/Pre}$ values of all sample areas, and we select sample areas from the control group that have a larger $RMSPE_j^{Post/Pre}$ value than the treated group area and whose $RMSPE_j^{Pre}$ value is less than or equal to twice the $RMSPE_j^{Pre}$ value of the treated group area. The selected control area and treated group area are called ‘significant samples’ . Finally, we divide the significant number of samples n by the total number of samples N, and its value is the ‘significant effective value’ of the policy effect of the j region in the passenger volume per capita indicator.

Based on the steps of policy effectiveness testing, we separately test the policy effect estimators of the treated group's passenger volume per capita index. The results are shown in Table 3. It can be seen from Table 3 that only the ‘significant effective value’ of the policy effect in Beijing, Tianjin, and Nanchang reaches a significant level.

Table 4. Treated group policy estimator validity test result

Cities in treated group	$RMSPE_j^{Pre}$	$RMSPE_j^{Post}$	$RMSPE_j^{Post/Pre}$	Significant sample (n)	Total samples (N)	Significant effective value (n/N)
Beijing	2.339	590.204	252.286	1	38	0.026**
Shijiazhuang	1.737	62.621	36.049	26	38	0.684
Taiyuan	1.106	60.762	54.934	20	38	0.526
Dalian	1.821	182.810	100.384	12	38	0.316
Harbin	0.899	49.600	55.190	18	38	0.474
Nanjing	0.625	113.979	182.228	7	38	0.184
Jinan	1.422	77.726	54.666	23	38	0.605
Zhengzhou	2.587	220.682	85.305	14	38	0.368
Wuhan	6.649	164.889	24.798	34	38	0.895
Changsha	10.723	1113.622	103.856	12	38	0.316
Shenzhen	2.162	131.432	60.786	19	38	0.5
Chongqing	0.032	26.025	801.604	10	38	0.26
Kunming	3.205	114.918	35.860	29	38	0.763
Xi'an	0.314	53.860	171.691	4	38	0.105
Urumqi	1.880	176.940	94.105	13	38	0.342
Tianjin	0.041	106.370	2585.567	1	38	0.026**
Hohhot	3.729	147.015	39.422	25	38	0.658
Shenyang	1.462	163.027	111.517	6	38	0.158
Changchun	4.047	141.454	34.949	25	38	0.658
Shanghai	1.461	25.266	17.298	30	38	0.789
Ningbo	0.458	73.873	161.381	4	38	0.105
Hefei	0.934	273.398	292.608	4	38	0.105
Fuzhou	1.801	227.308	126.236	6	38	0.158
Nanchang	0.181	84.833	469.376	1	38	0.026**
Qingdao	1.668	41.277	24.745	29	38	0.763
Guangzhou	1.368	31.594	23.093	30	38	0.789
Haikou	1.210	113.282	93.655	11	38	0.289
Guiyang	0.487	43.512	89.366	7	38	0.184
Lanzhou	1.666	79.626	47.808	23	38	0.605
Xining	3.331	143.124	42.968	24	38	0.632
Yinchuan	2.656	104.380	39.307	24	38	0.632
Baoding	1.592	94.497	59.376	22	38	0.579
Suzhou	2.081	82.997	39.883	24	38	0.632

Hangzhou	1.121	133.748	119.353	6	38	0.158
Xinxiang	0.884	10.838	12.264	27	38	0.711
Zhuzhou	6.540	123.690	18.912	32	38	0.842
Liuzhou	4.323	111.757	25.853	31	38	0.816

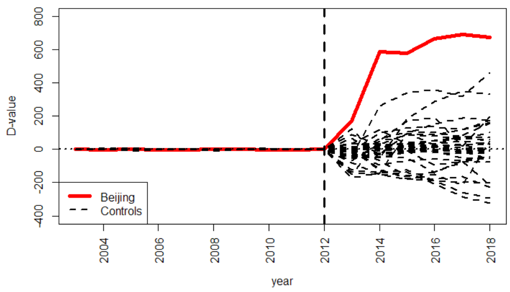
Note: ***, **, * indicate the significance level of 1%, 5%, and 10%

The significant distributions of ‘fitting error value’ and ‘prediction error value’ in the treated group are shown in Figure 2. At the same time, the distribution of the ‘fitting error value’ and ‘forecasting error value’ of the passenger volume per capita index whose $\mathrm{RMSPE}_j^{\mathrm{Pre}}$ value is less than or equal to twice the $\mathrm{RMSPE}_j^{\mathrm{Pre}}$ value of the treated group area is also displayed accordingly. In Figure 2, the solid line and the dotted line on the left side of the vertical line represent the trend line of ‘fitting error value’ in the treated group and the control group, respectively, while the solid line and the dotted line on the right represent the trend lines of the ‘prediction error value’ in the treated group and the control group respectively.

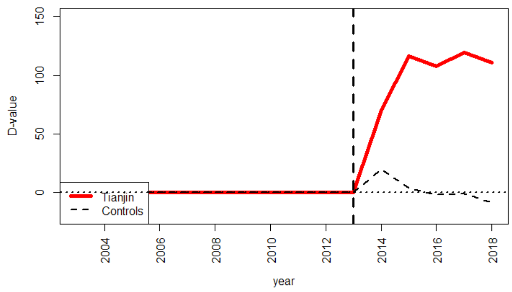
It can be seen from Figure 2 that before the demonstration project was established, the distribution of ‘fitting error values’ between all treated groups and control groups was relatively small. However, after the establishment of pilot cities, the gap between the ‘prediction error value’ in the treated group and the control group began to increase.

First of all, it can be seen from Figure 2(a)(b) that after 2012 and 2013, the ‘prediction error value’ (‘policy effect’) of Beijing and Tianjin showed a significant increase and a positive situation due to the establishment of demonstration projects. From a practical point of view, we believe that this situation is mainly related to Beijing and Tianjin's vigorous development of rail transit and optimization of ground public transportation systems. Specifically, Beijing’s track operating mileage in 2012 is 433.8 km, with 779 bus and tram lines; Tianjin’s track operating mileage in 2013 is 136.45 km, and bus and tram lines are 566; In 2018, Beijing has 600.64 km of track and 856 bus and tram lines, and Tianjin has a track operating mileage of 222.22 km and 926 bus and tram lines. The expansion of rail transit and the optimization of the ground public transportation system have further increased public transport in the city travel choice rate. Therefore, after 2012 and 2013, the passenger volume per capita of Beijing and Tianjin has been significantly higher than the counterfactual value, and the policy effect has appeared to be positive. In terms of travel services, the quality of Beijing's rail transit services has improved significantly, and the structure of the bus network has been continuously optimized. Bus network coverage is also constantly optimized and expanded, and the shortest service interval will ensure that within 2 minutes. The train punctuality rate reaches 99.9%. During the policy period, Tianjin further optimized the bus network, improved the connection with the subway system, opened 30 bus lines to connect subway, optimized the adjustment of more than 40 bus lines around the subway, and realized the ‘zero distance’ transfer of all subway station points.

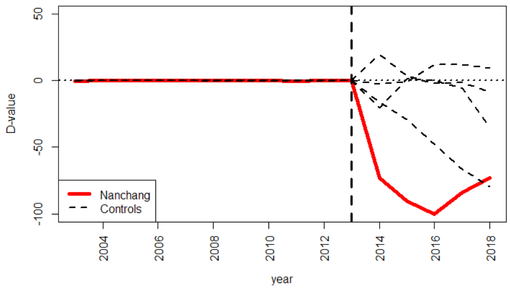
From Figure 2(c), after 2013, the ‘prediction error value’ of Nanchang has been negative after the demonstration project was established. Intuitively, the establishment of the demonstration project should promote the passenger volume per capita in Nanchang, but during the period it produces a negative effect, which is contrary to expectations. We believe that this situation is mainly caused by two reasons. On the one hand, as the capital of Jiangxi Province, Nanchang has attracted a large number of migrants to entrepreneurship in Nanchang. According to the statistical yearbook, it can be seen that the total population of Nanchang's municipal districts increased from 2.301 million in 2014 to 3.05 million in 2015. It has increased throughout the following years. and the rapid increase in population has a huge impact on the public transportation system of Nanchang. At the same time, since 2015, the passenger volume of the ground bus system in Nanchang has dropped significantly, from 617.73 million in 2014 to 391.03 million in 2017. However, the passenger volume of Nanchang Rail Transit only increased from 79.58 million in 2016 to 141.77 million in 2018. As the provincial capital city, Nanchang opened its first rail transit line in 2015. By 2019, Nanchang Metro is operating a total of 2 lines, including 2 lines under construction, operating 60.35 kilometers, and is located in the fourth echelon of subway construction. Rail transit construction requires more capital investment. Therefore, in the initial stage, the growth rate of rail transit passenger traffic is slower than the decline rate of ground public transportation passenger traffic. This situation causes the actual value of Nanchang's passenger volume per capita to be lower than its counterfactual value. On the other hand, cities unselected for demonstration projects are also developing public transportation to further increase their public transportation passenger traffic sharing rate. Finally, the superposition of the above two factors makes the policy effect of Nanchang's passenger volume per capita significantly negative. On the other hand, the planning of ground transportation and rail transit needs to be further optimized. For example, the Bus Rapid Transit system (BRT), building in Nanchang in 2015, has problems during commissions, such as various vehicles traveling in the BRT channel and the absence of overpass to guide people, causing congestion on the BRT channel. Finally, the combination of the above two factors makes the effect of Nanchang's per capita passenger transport policy negative.



(a) Beijing



(b) Tianjin



(c) Nanchang

——treated ----controls

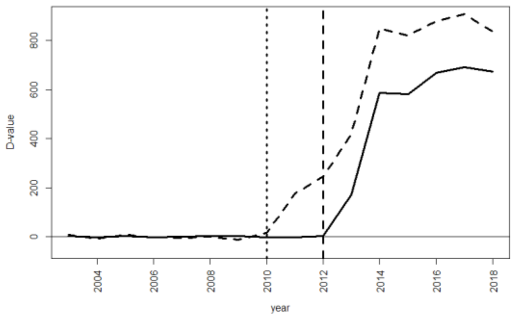
Figure 2 Fitting error distribution of treated group and control group with ‘significant policy effect’

4.3 Robustness analysis of policy effects

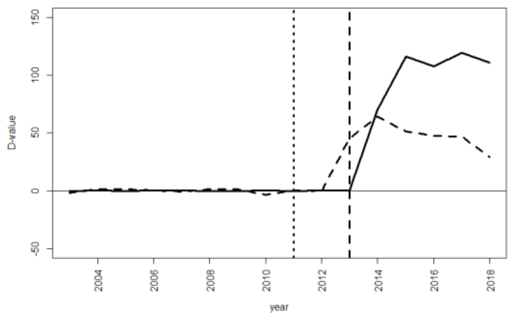
This part adopts a ‘time placebo test’ and ‘leave-one-out’ to further test the robustness of the above three ‘significantly effective’ index estimates. The ‘time placebo test method’ assumes that the time of setting up demonstration cities in Beijing, Tianjin, and Nanchang is two years earlier than the actual time. Then, at this ‘hypothetical point in time’, re-evaluate the policy effects of the establishment of pilot cities on the passenger volume per capita indicators in these areas. If the fit level and policy effect estimates under the ‘hypothetical time point’ have not changed significantly compared with the ‘true time point’, it shows that the result of policy effect estimation will not change with the artificial choice of the establishment time point, so it has certain stability. ‘Leave-one-out robustness’ is to test the sensitivity of the experimental group to the weight change of the control group. We iteratively delete a city in the control group of the model to check whether the composite result is affected by a specific city, thereby assessing the influence degree of the city in the specific control group on the synthesis result.

Figure 3 shows the results of the time placebo. The solid line reflects the fitting error and prediction error before and after the ‘true time point’. The dotted line reflects the fitting error value and prediction error value before and after the ‘hypothetical time point’. It can be seen from Figure 3(a) that the fitting error value of Beijing's passenger volume per capita (dotted line) fluctuates more violently on and off the zero level before the ‘hypothetical time point’ than the fitting error value under the ‘real-time point’ in 2012 (solid line). The R^2 value of the control group corresponding to the ‘hypothetical time point’ is 0.9713, which is far from the R^2 value 0.998 under the ‘real-time point’. This shows that the fitting situation of the control group under the ‘hypothetical time point’ is much worse than the fitting situation under the ‘real-time point’. It can be considered that the policy effect of Beijing's passenger volume per capita based on the ‘real moment’ in 2012 is more reliable than the result under the ‘hypothetical timing’ two years in advance. The R^2 values of the control group in Tianjin and Nanchang under the ‘hypothetical time point’ in 2011 are (0.9941, 0.9988), the level of fit is lower than the R^2 value (1, 1) under the ‘true time point’ in 2013. Similar to the robustness analysis logic of Beijing's passenger volume per capita, it can be directly determined that the policy effects of Tianjin and Nanchang's passenger volume per capita under the ‘real-time point’ are more reliable than the results under the ‘hypothetical time point’ two years in advance.

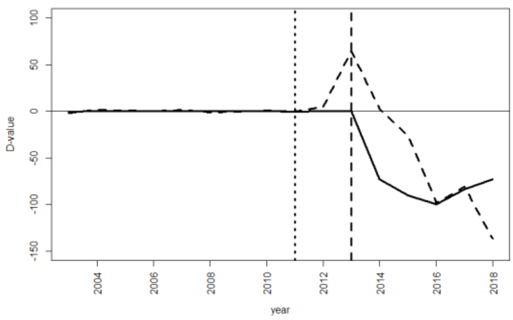
Figure 4 shows the results of the leave-one-out robustness, the solid line is the actual value of passenger volume per capita before and after the demonstration project, the dashed line is the counterfactual value of passenger volume per capita before and after the demonstration project, and the light line is the counterfactual value after iteratively deleting a city in the model control group. It can be seen from Figure 4 that deleting any city from the best control group of Beijing, Tianjin, and Nanchang will affect the counterfactual values of Beijing, Tianjin, and Nanchang. This means that the counterfactual values of Beijing, Tianjin, and Nanchang are not driven by a specific city.



(a) Beijing



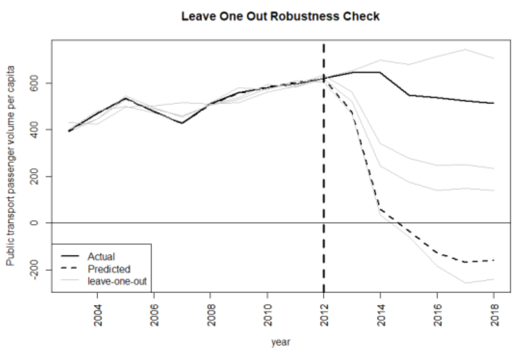
(b) Tianjin



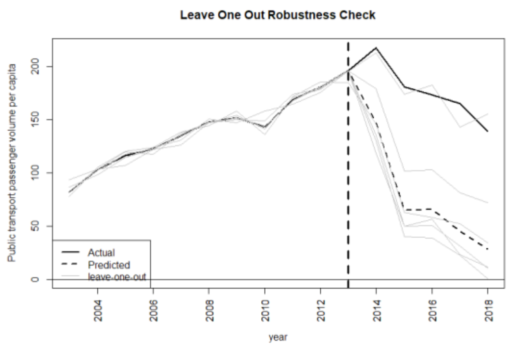
(c) Nanchang

——Real-time point synthesis error ---- Hypothetical time point synthesis error (placebo)

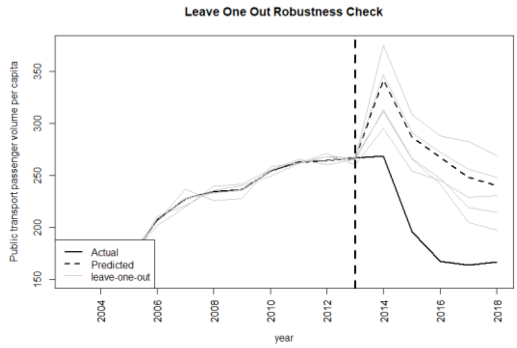
Figure 3 The ‘Time Placebo Test’ of Policy Effectiveness



(a) Beijing



(b) Tianjin



(c) Nanchang

Figure 4 The ‘Leave-one-out Robustness’ of policy effects

Through the above tests, we believe that the establishment of the demonstration project has certain robustness in the estimation results of the policy effects on the passenger volume per capita indicators of Beijing, Tianjin, and Nanchang.

5. Conclusions

This paper uses the panel data of 74 cities from 2003 to 2018 to investigate the quasi-natural experiment of the transit metropolis demonstration project, based on HCW to test the impact of the transit metropolis demonstration project on the passenger volume per capita in the pilot cities. This is the first time that the HCW method has been applied to the analysis of traffic policy effects. This method does not try to estimate those unobservable factors, but uses the available data to replace factors, thereby providing a new method and perspective for policy evaluation under complex mechanisms and limited data conditions. The study uses the HCW method to evaluate the effect of China’s Transit Metropolis policy. This HCW-based method has the following advantages: (1) There is no need to consider the sample selection effect, and it has greater flexibility. (2) It only uses the information of passenger volume per capita, which does not need other covariates. The parameter estimation is simple, and the results have good robustness. (3) There is no limit to the value of the coefficient, which can be negative. The fitting equation can take into the extremes of the treatment group, which improves the applicability and accuracy of the model. From the fitting results, the counterfactual value of the HCW method before the policy has a high degree of fitting with the true value, which shows that the HCW method is effective in evaluating the effect of the policy.

Among the 37 urban passenger volume per capita indexes composed of the first and second experimental groups, the policy effect of passenger volume per capita index in three regions reaches a significant effective level. It could be inferred from the results that: (1) Except for Beijing, Tianjin, and Nanchang, other cities in the treated group are failed to pass the significance test. Therefore, in this experiment, the effect of the demonstration project on the passenger volume per capita of the treated group is invalid. (2) Beijing and Tianjin passed the goodness of fit and estimation accuracy test and passed the validity and stability test. This shows that the establishment of demonstration projects has a positive effect on the passenger volume per capita in Beijing and Tianjin. If increasing passenger volume per capita is a policy goal, the demonstration project models in Beijing and Tianjin have reference value. (3) From the perspective of passenger volume per capita in Nanchang, a large influx of people has an impact on the passenger volume per capita index. Compared with Nanchang, Beijing and Tianjin have a good foundation in rail transit, so after the implementation of the policy, the passenger traffic of Beijing and Tianjin has risen sharply, while the passenger traffic of ground transportation has declined.

Based on the above findings, this paper proposes the following countermeasures: The first is to further accelerate the construction of rail transit and further tap the potential of rail transit. Rail transit has significantly increased passenger volume per capita. Carry out urban development planning according to the mainline of Metro, the land near the subway platform should be reserved and developed as a whole. According to the subway platform, the bus lines should be optimized and the supporting infrastructure should be improved. The second is to optimize and improve the ground public transportation system and improve the quality of public transportation services. Public transit cities need to be people-oriented and improve the passenger travel experience by optimizing and adjusting the ground public transport network, strengthening the connection with rail transit, increasing operating vehicles, and increasing operating time. The third is to improve the public transport financial subsidy mechanism. Improve the public transportation financial subsidy mechanism to further maintain and promote the development of public transportation. Investigate and analyze the cost, profit, and loss of different routes, and formulate targeted subsidy policies or methods to enhance the competitiveness of public transportation. The fourth is to guide and restrict the use of cars. With car purchase restrictions as the core, combined with car restrictions, car purchase tax adjustments, car pollution fees, and parking fees, various policies are integrated to control the increase of vehicle number and to optimize the spatial and temporal distribution of vehicles on urban road network.

Acknowledgments

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