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Does High-Speed Rail Really Have a Positive Effect on City Consumption? A PSM-DID Approach With China Case

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ABSTRACT

This paper evaluates the treatment effect of high-speed rail (HSR) operation on city consumption using the dataset of Chinese cities from 2003 to 2019. Firstly, the applicability of observations is discussed; secondly, observations with no appropriate contrast samples are dropped for more precise empirical results. Then, propensity score matching (PSM) is implied to have the database much more balanced and suitable for the difference-in-difference (DID) framework, that is, the PSM-DID approach. The main results find a novel phenomenon of Simpson's paradox regarding the HSR-consumption nexus, which indicates that even though we can observe the positive effect on the whole, the results argue negative relationships between HSR and consumption within subclass cities. In addition, a dose-response assessment (DR) and some other checks have been proposed to demonstrate robust estimation results.

KEYWORDS

High-Speed Rail; City Consumption; PSM-DID; Dose-Response; Simpson's Paradox

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1. Introduction

The boom of high-speed rail (HSR) is regarded as the next wave of economic growth (Qin, 2017; Shao et al., 2017). the current state of regional consumption may have been encouraged- although remaining a much-debated topic- by this extensively implemented high-speed technology (Meng et al., 2018) in China. The report of the 19th National Congress of the Communist Party of China clearly stated that it is necessary to "improve the institutional mechanism for promoting consumption and enhance the basic role of consumption in economic development." The consumption sector has once again received the focus and support from policies, and HSR is one of the most apparent political tools for the central government of China to reshape the spatial economic distribution and enhance and stimulate domestic demand. Therefore, knowing more about the relationship between HSR and consumption is thus crucial for academics, government policymakers, and implementers.

The expansion and connectivity of HSR networks as an important political tool to promote spatially balanced economic development in China's regions (Bosker et al., 2018) has allowed the public to contribute to a larger domestic demand market with the aid of convenient transportation. Thus a new phrase, "internal demand for high-speed rail," has gradually emerged. Therefore, consumption, the one key component of domestic demand, will also change in aspects of regional disparities and dynamic trends as the adjustment of spatial economic redistribution brought by HSR. Therefore, it is a meaningful topic worth studying to promote the coordinated development of all regions in China. However, previous studies discussing factors affecting consumption and demand have mainly explained changes in government tax expenditures and investment (D'Acunto et al., 2017; Ercolani and Valle e Azevedo, 2014), savings and crowding out effects (Funashima and Ohtsuka, 2019; Reinhart et al., 2016). That said, little attention has been paid to infrastructure development, such as high-speed rail. Correspondingly, the authors have addressed some aspects regarding HSR and regional affairs, such as regional economic growth (Yin et al., 2015) and social development (Geng et al., 2015). Furthermore, they argue that HSR is an important economic and social driver for the central government (Mu et al., 2015), as it can improve travel convenience and increase employment opportunities. Nevertheless, still, there is limited research concerning rail transport and consumption demand, which is precisely the literal gap this paper intends to fill.

Consumption is an important engine and support of China's economic growth, commonly affected by spatial policies and factors like transportation (Donaldson, 2018; Donaldson and Hornbeck, 2016). As a revolutionary technological transportation application, HSR is particularly important and exerts a crucial impact on cities' consumption and HSR networks. With the coming of the "HSR era," China's regional economy is seeing spatial transfer, capacity expansion, and upgrading for the promoted allocation effectiveness of factors between cities and regions owing to the operation of HSR (Zhu et al., 2016). It seems to provide us with a new impetus to stimulate consumption growth. Growing studies are dedicated to evaluating HSR's contributions to economic growth (Ke et al., 2017; Long et al., 2018; Qin, 2017; Zheng and Kahn, 2013). However, little attention has been paid to the treatment effect of HSR on consumption in China. HSR is recognized as an increased supply of transportation tools (Dong, 2018) that will have spillover effects on economic activity (Ahlfeldt and Feddersen, 2018), housing prices (Zheng and Kahn, 2013), economic distribution (Qin, 2017) and tourism development (Pagliara et al., 2017). Thus it is natural and reasonable to reveal the impact of HSR on domestic demand, especially the consumption of cities. In this paper, regarding the intervention of HSR in Chinese cities, we care about two fundamental questions. For the first one, does HSR affect city consumption along the network routes? If dose, then is the impaction stimulating or inhibiting? Existing studies have concluded that the relative impact of HSR on regional activities, including consumer behavior, is debated for countries or regions that are subject to the "radiation effect" and the "siphon effect" of HSR at the same time (Dong, 2018; Dong et al., 2019). For the second one, how can we evaluate the effects of HSR on consumption? Previous studies have documented that a difference-in-difference quasi-experimental strategy can be accessibly employed to evaluate causal effects of programs or policies (Card and Krueger, 2000), correspondingly, that counterfactual model has been widely used to measure the exact impact of HSR (Albalate et al., 2017; Albalate and Fageda, 2016; Long et al., 2018; Shao et al., 2017), however, when we employ this framework to China case, there are some methodological details needed to be noted: (a) HSR networks are constructed gradually year by year, thus cities are not intervened at the same time point as a classical DID model specified; (b) existing studies on HSR, especially using samples from China, usually incorporate all observations into the model, regardless of the comparability of cities; (c) and mostly we may have another strong assumption that all cities suffer the same level of treatment effect, no matter there are significant difference in intervention concentration - the development level of HSR.

Therefore, an empirical evaluation is urgently needed on the performances of HSR impacting consumption, especially in the case of China. Our significant contribution is to empirically ascertain to what extent HSR affects consumption scale using a dataset of Chinese cities from 2003 to 2019. We employed a generalized DID model as the basic analyzing framework, which can be used to evaluate the adoption of staggered policy (Almond et al., 2018; Kudamatsu, 2012). We first dropped specific observations with no appropriate contrast samples to obtain a precise estimator. Then we employed a PSM method to enhance the balance condition of the counterfactual estimation under the treatment of HSR operation since various confounding factors may affect the evaluation of treatment effects. Finally, we constructed a PSM-DID analysis to seek a more credible evaluation result. It is one key component that makes our paper different from existing works. In addition, this paper also aims to portray a DR assessment (Hirano and Imbens, 2005) to examine the heterogeneous effects of HSR and control the self-selection bias and endogenous problem. There are often some commonly and latently composed assumptions when evaluating the effects of HSR. One of them is that the effect level is the same over time and across cities, but this assumption is too strong. Therefore, another critical component that makes our work a seminal study in comparative research is to relax that assumption. Results show that HSR generally has a stimulatory effect on the consumption scale expansion of Chinese cities, and if balance conditions are not considered, treatment effects are often overestimated; furthermore, the visualized results of the DR assessment show that there is an apparent s-shaped response function of HSR development on the scale of consumption. This paper provides a new perspective for re-examining the impact of traffic infrastructure on urban consumption scale expansion and argues that governments should consider the varying latent responses of cities when using HSR to promote consumption development.

The rest of the paper is organized as follows. Section 2 reviews some related literature on HSR and consumption. Section 3 contains the empirical strategy description with the quasi-experimental framework, in which the set of the counterfactual method and the corresponding parallel trend test is introduced; then, a simple description of variables and data. The empirical results and subsequent discussions of findings are presented in Section 4, especially the heterogeneity of the relationship between HSR and consumption. Finally, Section 5 concludes the impact of HSR on consumption.

2. Literature Review

Domestic demand, especially consumption, has become the most crucial driver for growth (D'Acunto et al., 2017). Studies have demonstrated the impact of HSR on economic growth(Li et al., 2018; Long et al., 2018) and the accessibility of regions (Xu et al., 2018). However, little attention has been paid to the relationship between HSR and consumption. In this paper, we will undertake a quasi-experimental study to test this relationship in detail. The comparative literature review can be organized from aspects of public investment, including infrastructural investment and transportation.

Previous studies have focused on fiscal policies on the expansion of consumption. For instance, some authors pointed out that financial investment is an essential macroeconomic control tool for governments to stimulate domestic demand and consumption (D'Acunto et al., 2017; Ercolani and Valle e Azevedo, 2014). Among them, studies related to public investment and transportation infrastructure are the basic materials of this paper.

Many existing studies have discussed the relationship between public investment and consumption by testing the crowding-out and crowding-in effects (Andrade and Duarte, 2016; Heutel, 2012) but without a unanimous conclusion. Lewis and Winkler (2017) believed that public investments would increase consumption in the private sector, but some authors argued a crowding-out effect (Funashima and Ohtsuka, 2019). Some Chinese scholars have conducted empirical analyses on the relationship using samples of China provinces and cities, and they believe there are both complementarity and substitution effects. Thus the impact is different and multi-leveled in the various conditions (Dawood and Francois, 2018; Lewis and Winkler, 2017). In addition, Turnovsky and Monteiro (2007) found that it might be a crowding-out effect for the public expenditure on private consumption in the short run but a crowding-in effect in the long run. Zhang and Meng (2021) conducted a numerical simulation and argued that the crowding-out effect dominates in current China. Some studies are naturally close to ours on the pulling effect of infrastructure investment on consumption. Some studies have concluded that infrastructure investment can be helpful for consumption (Jiang et al., 2017). As Chen and Yao (2011) argued, infrastructure investment may have both a stimulating effect and an inhibitory effect on consumption based on existing studies. Meanwhile, studies pointed out that the effects differ by infrastructure investment type (Zhang et al., 2013), and effects may be time-varying (Chen and Yao, 2011).

Papers studying the consumption from aspects of transportation infrastructures are gradually emerging but in much smaller quantities. Transportation infrastructure should significantly impact economic development and social consumption compared to other types of infrastructure (Dong, 2018; Shao et al., 2017), for it brings essential convenience to regional activities (Dong et al., 2019; Xu et al., 2018). The convenience increases the concentration and agglomeration of productive elements and industries (Cao et al., 2019), so the transport infrastructure development will incentivize consumption growth by increasing income and creating demand.

Regarding the role of transportation infrastructure, more attention is paid to regional economic growth and poverty reduction, but few papers have directly discussed its impact on consumption. For example, using data from the Philippines and Papua New Guinea, researchers empirically argue that better traffic development is beneficial for poverty reduction, and the mileage of roads is positively correlated with the income increase of the poor (Balisacan and Pernia, 2002; Gibson and Rozelle, 2003). Donaldson (2018) found that, in India, the agricultural income of farmers in areas with railway connectivity is 18% higher than in areas without railroad connectivity. Pereira and Andraz (2004) verified the positive external effects of highway construction on providing employment opportunities and promoting agglomeration. They examined the direct and indirect effects of roads on the welfare of the poor and found that every 1 % increase in road accessibility will increase the income of the poor by 0.32 %. In terms of consumption, it is believed that consumption is based on various material foundations, and transportation infrastructure can speed up the circulation of population, capital, and commodities in space, thereby increasing the consumption demand (Aker and Mbiti, 2010). Furthermore, the effect of improved transportation will also be passed on to the consumer through commodity prices and transaction costs (Donaldson, 2018). Therefore, improving the construction of transportation facilities is considered an effective way to promote the development of consumption.

China has ranked first in the mileage of HSR worldwide, and it will intuitively impact consumption expansion and spatial re-adjustment. With the HSR network's connection, cities' integration effects have led residents to shift their consumption to the regional central cities along the routes and even take "cross-province shopping" (Diao, 2018). Such conveniences will intensify the redistribution of demand, thus affecting the development of cities' consumption scale.

The impact of HSR on consumption development is seemingly apparent. However, we still do not know the exact direction of its impact, especially when considering the differences between cities with varied sizes (Qin, 2017). Many studies have paid attention to the contribution of HSR to regional development through rising urbanization, house prices, and market integration (Ke et al., 2017; Long et al., 2018; Zheng and Kahn, 2013). Furthermore, empirical evidence has been discussed based on Europe, Asia, and other regions (Shao et al., 2017). Moreover, HSR has a more considerable pull on large regional cities than small ones (Dong, 2018; Long et al., 2018), meaning a restriction of consumption for some cities and driving a consumption outflow to bigger ones.

All in all, both a negative and a positive effect can be expected. In this paper, we do not think the operation of HSR for central cities like mega-cities and provincial capital cities is as exogenous as for others. Therefore, it is more convincing to have the observations of big cities excluded, and meanwhile, those big cities also lack corresponding control group samples under the DID framework. Details will be discussed in the next section. Nevertheless, few studies have empirically measured the effect of HSR on consumption expansion, and it remains unclear how much it has impacted China. This study attempts to fill this gap using more precise methods and identification strategies.

3. Methodology and Data

3.1. Background and Identification Strategy

We will reveal the treatment effects of HSR operations on the consumption scale expansion of cities across China. The rapid development of HSR has brought China into a new era of spatial development and has provided significant effects in promoting economic growth, spillover, and mobility (Ke et al., 2017; Long et al., 2018; Shao et al., 2017). According to the China State Railway Administration, the mileage of HSR reached 29,000 km by the end of 2018. The HSR network has expanded so fast that it has dramatically shortened the travel time between adjacent cities (Dong, 2018). Moreover, it represents the world's most extensive network under operation (Long et al., 2018). The Mid-to-Long Term Railway Network Plan, which was first approved in 2004 and then updated in 2008, shows us a Four Vertical and Four Horizontal plan across the whole country to connect all the provincial capitals and important cities (Dong, 2018).

Further, a larger Eight Vertical and Eight Horizontal grid are drafted. Currently, most regional central cities have been covered by HSR, and the HSR mileage reached 37,900 km by the end of 2020, with more than 80 percent of major cities being connected. Moreover, HSR has fostered socioeconomic changes all over China since it facilitates cross-city integration. Thus, it is reasonable to impact the consumption expansion of cities.

The difference-in-difference model (DID) is recognized as one of the most popular approaches (Card and Krueger, 2000; Moser and Voena, 2009) to calculating the causal effects. This paper applied this model since HSR operation can be seen as a quasi-experimental event. One of the advantages of using this method is that it can control and eliminate general factors that affect consumption changes and control the unobservable variables that do not change with time, thus obtaining more reliable estimates. As a result, the DID framework has been widely used in studying HSR-related nexuses.

Generally, three types of information are required: treatment or intervention, outcome, and control group. The availability of running HSRs helped us to distinguish cities into treatment and control groups and to provide pre- and post-intervention status. The city's consumption is the outcome, which should differ between the treated and the control when HSR significantly impacts consumption. However, some model setting details still need to be confirmed. Firstly, as HSR stations and lines are not operating at the same time point in China, thus a standard DID model with only two periods may not be enough. As a solution, we employ a generalized DID (Autor, 2003) to estimate the treatment effects of HSR on consumption to deal with the gradually happening intervention impact, or in other words, when treatment varies over time. In this situation, the baseline empirical model takes the following two-way fixed-effects panel data model shown in Equation (1). In addition, we utilize year-fixed and city-fixed effects to control for the invariant city attributes and time attributes (Moser and Voena, 2009).

$$consumption_{it} = c + \beta \times HSR_i \times Post_t + B \times Controls_{it} + \alpha_i + \theta_t + \varepsilon_{it} \quad (1)$$

Where consumptionit is the outcome variable of the city i in time t, it is represented by the total retail sales of consumer goods. The variable HSRi is a binary indicator distinguishing the treated group and untreated group, with HSRi equals one if city i has at least one HSR line/station in operation during the research period; otherwise, it equals zero. Postt is a dummy denoting the state before or after the HSR intervention, and it takes value one for time t after the operation. The interaction term HSRi × Postt captures the treatment effect of HSR. Controlsit is a vector of control variables containing the time-varying city-level characteristics, such as industry structure, population, wage, finance, savings, and others, which will be listed in Table 1. Parameters αi and θt are the city-fixed and time-fixed effects, respectively; they can help control for macroeconomic or political shocks, and εit denotes the random error. Then, the coefficient β is the DID estimator indicating the treatment effect.

The validity of a generalized DID with a multiple-period case relies on the satisfaction of the parallel trend hypothesis. Namely, the consumption dynamics in cities with and without HSR should have a similar pre-trend over time. Only then can the counterfactual value of consumption be calculated according to the value of the control group cities, then the average treated effect can be obtained by subtracting. Although there have long been critical discussions over the test for parallel trends (Autor, 2003; Moser and Voena, 2009), a potential challenge is that preexisting disparities in the time trend of consumption may drive the differential changes between HSR cities and non-HSR cities. To address this issue, this paper allows β to vary in time in two ways: (a) allow β to vary across treated and control subclasses prior to the HSR, using 2008 as the baseline as the first railway speed up to 200 km/h operated in 2008, the coefficients can be derived from Equation (2), we call it MV2012 method in this paper for short; (b) employ an event study model to capture the dynamic effects of HSR on city consumption, Equation (3).

$$consumption_{it} = c + \sum_{t \neq 2008} \beta_t^t \times HSR_i \times Yea\_t + \sum_{t \neq 2008} \beta_t^c \times non\_HSR_i \times Yea\_t + B \times Controls_{it} + \alpha_i + \theta_t + \varepsilon_{it} \quad (2)$$

$$consumption_{it} = c + \sum_{k=-m} \beta_t^t \times HSR_i \times Yea\_t + \sum_{k=-m}^{q} \beta_k \times HSR_i \times IF(\tau = k) + B \times Controls_{it} + \alpha_i + \theta_t + \varepsilon_{it} \quad (3)$$

Where the superscript of β in Equation (2) indicates treated (superscript t) or control group (superscript c); Yea_t is year dummy variable for year t; for example, Yea_2010 will equal one in 2010 and zero in any other years. τ in Equation (3) is a newly generated time variable relative to the operation year of HSR in certain cities, so in the operation year τ = 0, and we use k standing for the value of τ, and use IF(τ = k) as an indicator to replace the original term Post. Here, IF(τ = k) returns one when τ= k; otherwise, zero.

Additionally, to have a more precise estimation, the PSM method is introduced to have the observation more randomized across cities before applying the generalized DID, the so-called PSM-DID method. The PSM method is commonly used in two-group data research and can help correct the influence of confounding factors. Finally, we compared the results before and after the matching. We found some basic conclusions, such as the treatment effects are prone to be overestimated if the observation bias is ignored.

3.2. Data and variables

Our empirical analysis is based on a panel dataset of cities in China from 2003 to 2019. Since there are many other factors affecting consumption besides HSR, it is necessary to have those factors controlled in empirical examinations. Referring to studies on the consumption-related nexus, variables in this paper are described as follows. Firstly, the dependent variable, denoted by consumption, is described by the value of "the total retail sales of social consumer goods" it indicates the domestic demand situation. It can be seen as the description of the consumption scale of a city.

Secondly, railway status information is needed to evaluate the impact of HSR on cities. Therefore, we prepared the data of HSR according to the information announced by the State Railway Corporation of China (SRC), China's National Railway Administration (CNRA), and the website www.12306.cn (12306, the official railway administration and train ticket website of China). Two critical elements of information are needed: a binary variable for whether the city has been treated by HSR and a time variable containing the year of being intervened. To have the dataset constructed, we sorted out the construction line data of HSR from the State Railway Corporation since 2003 in the first step, then recorded the time and cities covered for each HSR line in the second step. In the final third step, we confirmed each city's number of HSR lines/stations each year, referring to China's National Railway Administration and www.12306.cn. In our most precise specification, HSR equals one if the city has at least one HSR line/station. In alternative specifications, we have the number of lines/stations to portray the HSR development level of a city, denoted by HLS, thus telling the differences of cities in the endowment of HSR. Therefore, it helps us to have some heterogeneous intuition on the performance of the treatment effect of HSR.

Finally, the control variables are selected. Referring to previous studies on consumption nexus, we are going to include variables from aspects of industrial structure, population factors, financial factors, fiscal factors, and foreign direct investment. To capture variations of those factors, control variables in this paper a list here: (a) ind, the industrial structure measured by the share of the second and third industries of GDP; the quadratic term is also introduced to control the possible nonlinear effects (indsq); (b) lnpop, the logarithm of the total population of cities by the end of each year; (c) lnwage, the logarithm of the average wage of employees; (d) lninv, the logarithm of city's total fixed assets investment; (e) lnsave and lnloan, the logarithm of financial institution's deposit and loan at the end of the year respectively; (f) fratio, the degree of fiscal decentralization, fiscal resources might have an impact on consumption scale of cities, we use the ratio of "local fiscal budget revenue/local fiscal budget expenditure" to describe it; and (g) lnfid, the logarithm of the actual foreign investment, it represents the openness of cities' economy. Moreover, we will introduce the time-fixed and city-fixed effects to control the effects of possible underlying omitted variables that do not vary with time or change with cities.

Two primary data sources form the basis of this paper. The first one, as mentioned above, data on HSR is collected from the raw material and information from government or organization websites. The SRC is the main body of HSR line and station construction and discloses the progress and status of the construction, while the CNRA and 12306 have the information on the operation. Based on raw data from those institutions, we have collected the HSR data from 2003 to 2019, containing the name of cities, the operation statutes of HSR, and the number of lines/stations. The second one, characteristic data of cities, is drawn from the CSMAR research data services, China's largest, most accurate, and comprehensive financial and economic database. In addition, we collected the data we needed from the sub-database called Economic Research Series-Regional Economy.

Further, some missing data is supplemented according to the Statistical Yearbook of Chinese cities each year. We merged the HSR dataset and the city dataset using the names of cities and the year information. The initial merged dataset contains 286 prefecture-level cities. However, considering the missing data of variables and the missing observation in the time series, we dropped the cities with a sample data interval of less than six and samples with severe missing data. Finally, there are 4794 samples from 281 cities. Table 1 provides descriptive statistics of the main variables. Notice here that we divide Chinese cities into two broad categories, the big ones and the small ones, according to a third-party investigation report issued by the Rising Lab of China Business News Weekly (CBNW). Details will be shown in Section 4.1. So Table 1 reports the statistical information of all cities and small cities for comparison.

Table 1. Variables and the descriptive statistic. HSR: high-speed rail.

	All Cities			Small cities		
Name	Obs.	Mean	SD	Obs.	Mean	SD
consumption	4794	49.15	58.14	3961	31.32	30.90

HSR	4794	0.67	0.47	3961	0.60	0.49
HSR × Post	4794	0.22	0.41	3961	0.17	0.38
HLS	4794	0.73	1.93	3961	0.44	1.24
ind	4794	85.46	9.05	3961	83.47	8.60
indsq	4794	7385.70	1497.60	3961	7041.93	1395.61
lnpop	4794	5.87	0.66	3961	5.78	0.64
lnwage	4794	10.22	0.59	3961	10.16	0.58
lninv	4794	15.39	1.20	3961	15.14	1.08
lnsave	4794	16.07	1.21	3961	15.70	0.89
lnloan	4794	15.60	1.26	3961	15.20	0.90
fratio	4794	49.00	22.65	3961	42.44	17.98
lnfdi	4794	9.36	2.78	3961	8.85	2.73

4. Empirical Results and Discussion

4.1. Baseline results

Table 2 reports the treatment effects of HSR on city consumption estimated from Equation (1). In the base case, we include all available city observations (see columns (1), (2), and (3)). The results from the generalized DID method show that HSR operation might increase the consumption of cities on average. Comparing the estimators of DID terms, when variables have been controlled, the coefficient of HSR × Post will be slightly smaller than that when there are no control variables, with 24.15 and 21.77, respectively, and both significant at level 1%.

However, there may be an underlying defect that has not been taken seriously: the problem of the selection of candidate control group cities under DID framework. Ideally, each treatment group city should have a suitable control group sample. They should be relatively similar in economic and social development status, except that one has HSR in operation and the other has not. However, this condition is not necessarily satisfied in the scenario of this paper. We grouped cities into two main groups, big and small cities, according to the "Complete List of the Classification of Chinese Cities in 2017" (the name list of cities can be found at http://url.cn/5e0NQhN, and we call it LCC for short in this paper) to provide intuitive evidence. The LCC gives us five subclasses of Chinese cities, providing a comprehensive criterion to distinguish cities into two groups. (a) Big cities belong to subclass 1 and subclass 2 of the LCC, containing all provincial capitals, municipalities, and regional central cities; (b) small cities, the other periphery cities, which mostly do not have significantly superior performance. Then Figure 1 gives us direct and visible evidence of the underlying defect mentioned above. It shows each city's operational state of HSR under binary classification and five classifications. Here, we have two types of order of cities, ordered by GDP scale on the left side and ordered by operating time on the right side. The graphs clearly and visibly show no control group samples for big cities since all cities in the first subgroup had HSR in operation by the end of 2016. In other words, if these observations are included in the DID model, the treatment effects will be calculated based on the consumption differences between big and small city changes rather than reasonable counterfactual changes relative to the appropriate control group.

To improve the estimations, we decided to have the big cities dropped from our samples, and the estimates are reassessed as the comparing case in columns (3), (4), and (5) of Table 2. Moreover, we can see that the operation of HSR in cities is much more randomized according to the GDP scale, according to Figure 1. It makes our discussion more plausible. As a result, there is a significant decrease in the coefficient, with 8.13 compared to 21.49 in the base case. Conclusively, it is prone to overrate the treatment effect of HSR on consumption if central cities are included, which can be easily seen in the marginal effects of HSR in Figure 2. Nevertheless, on average, the operation seems to positively impact city consumption by 8.13 billion Yuan. This result is mechanically consistent with the many studies on the HSR-growth nexus since consumption is an essential component of the economy. Moreover, it is much more likely to be impacted by the HSR owing to the superiority of changing accessibility.

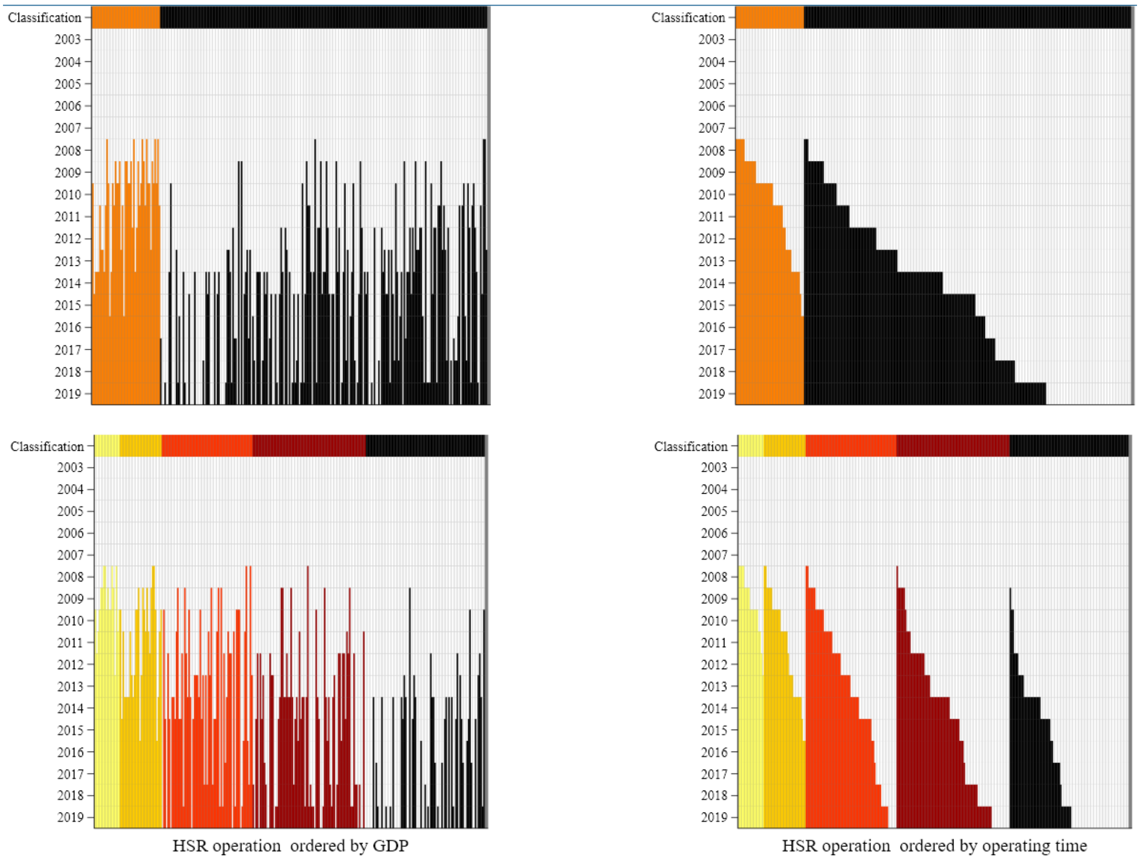

Figure 1. The operation state of HSR for each city.

Notes: for the upper part, it is the binary case with the color orange for big cities and black for small cities; and for the lower part, each color, in turn, refers to the five subclasses of cities from subclass 1 to 5.

For the control variables, we observe that the coefficients of most of them are significant and robust when comparing the two cases of estimation. ind has a significant adverse effect on the city's consumption but is likely to have a U-shaped nonlinear effect since the quadratic term is added into the model, with the coefficient of indsq equals 0.03 and the coefficient of ind equals -4.17, both significant at 1% level as listed in column (6). The population has a significant impact on consumption; with a 1% increase in population, there will be an increase of 31.42 billion Yuan in city consumption. The average wage seems to have little impact when we dropped the observations of big cities, with the coefficients of lnwage being nonsignificant. Finally, the city's investment may crowd out the consumption as the coefficient of lninv is negative and significant at the 1% level.

Furthermore, the financial developments seem to have no stimulative effect on consumption, residents may have a higher propensity to save rather than to spend, and loans are not meant to finance consumption. Finally, the coefficient of fratio is significantly positive, indicating that the degree of fiscal decentralization may give cities more autonomy to carry out local economic construction to promote consumption. In contrast, the openness of cities seems to have no significant impact on consumption when fixed effects of cities and years have been controlled. All in all, control variables have provided a robust performance in the nexus of HSR on consumption.

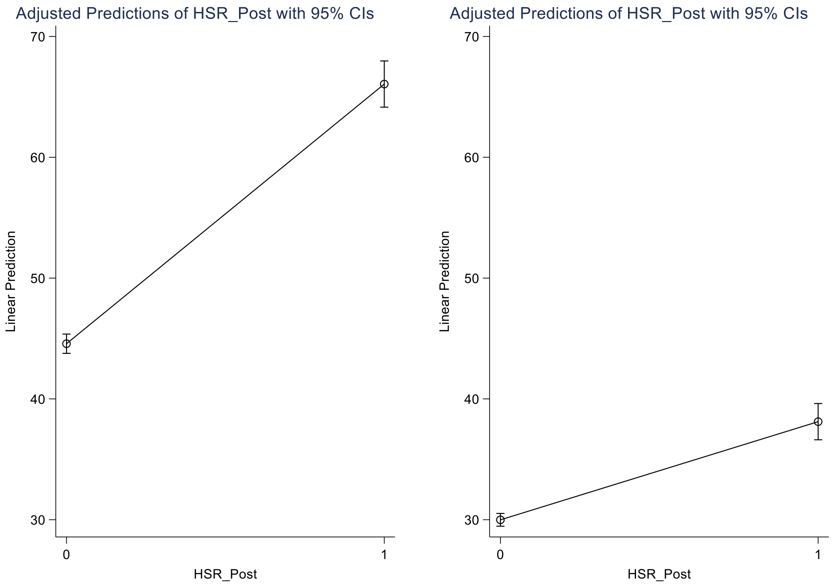

Figure 2. The marginal effects of HSR operation.

Table 2. HSR operation and city consumption: generalized DID method.

	Base case			Comparing case		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
HSR × Post	24.15***	21.77***	21.49***	8.55***	8.22***	8.13***
	(1.218)	(1.191)	(1.181)	(0.894)	(0.886)	(0.882)
ind		-0.68***	-9.49***		0.11	-4.16***
		(0.143)	(1.120)		(0.095)	(0.752)
indsq			0.06***			0.03***
			(0.007)			(0.005)
lnpop		44.02***	46.76***		29.46***	31.42***
		(6.836)	(6.788)		(5.958)	(5.936)
lnwage		-6.73***	-7.35***		-0.37	-0.79
		(1.734)	(1.722)		(1.403)	(1.397)
lninv		-13.02***	-12.92***		-5.34***	-5.25***
		(1.362)	(1.350)		(0.977)	(0.972)
lnsave		-6.74**	-7.91**		-7.99***	-8.48***
		(3.158)	(3.135)		(2.166)	(2.156)
lnloan		3.53*	2.85		-1.44	-1.75
		(1.811)	(1.798)		(1.322)	(1.316)
fratio		0.25***	0.17***		0.17***	0.12***
		(0.046)	(0.047)		(0.035)	(0.035)
lnfdi		-0.28	-0.18		-0.11	-0.06
		(0.234)	(0.232)		(0.154)	(0.154)
Constant	43.99***	156.98***	492.51***	29.92***	76.08*	235.11***
	(0.422)	(57.780)	(71.227)	(0.275)	(43.509)	(51.439)
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	4,794	4,794	4,794	3,961	3,961	3,961
R-squared	0.884	0.892	0.894	0.835	0.840	0.842

*Notes: Standard errors are in parentheses; *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.*

4.2. The Matching

The heterogeneity of cities is evident that it may lead to a biased DID estimator even though the counterfactual strategy can control for many biases. Therefore, we applied the PSM technology to correct the underlying bias before the generalized DID estimation. It allows us to select appropriate control group cities for the treated ones and control selection bias as much as possible. For the PSM, the dependent variable is the HSR. The independent variables are control variables listed in table 1 and other city-level variables, including population density, city area, and service share in GDP. The matching progress is carried out using the command psmatch2 with Stata 15.1.

Remarkably, some technical details about the PSM in this paper should be confirmed, particularly the way the weights are set. The initial PSM-DID method only deals with a two-section case (Blundell and Dias, 2009). The method matches observations in the first section and assigns the obtained weights to the corresponding samples in the following section. We are doing the exact matching, but in a multiphase case, the problem is whether we should treat samples before and after the HSR operation as two separate cross-sections. The answer should be no because if we do so and apply the PSM, we would get a matched sample from different years and cities, there will have much-mixed factors will be uncontrolled in the final model. To deal with it, we use a particular year before the HSR operation as the baseline for matching; since China has had its HSR network since 2008, we use 2007 as the baseline. After the PSM, we assign the obtained weights to all other years, so cities off support will not enter into the DID estimates.

The covariate imbalance testing graph, the propensity score histogram by treatment status, and the propensity scores' density curves before and after the matching are plotted in Figure 3. It shows that the standardized bias of most matched variables is less than 10%, and compared with the unmatched variables, the bias was significantly reduced. Meanwhile, we can see that, before the matching, the propensity scores of HSR cities and the control group cities are of different distributions; after matching, the two groups have similar probability density distributions, indicating that the characteristics of the cities are similar.

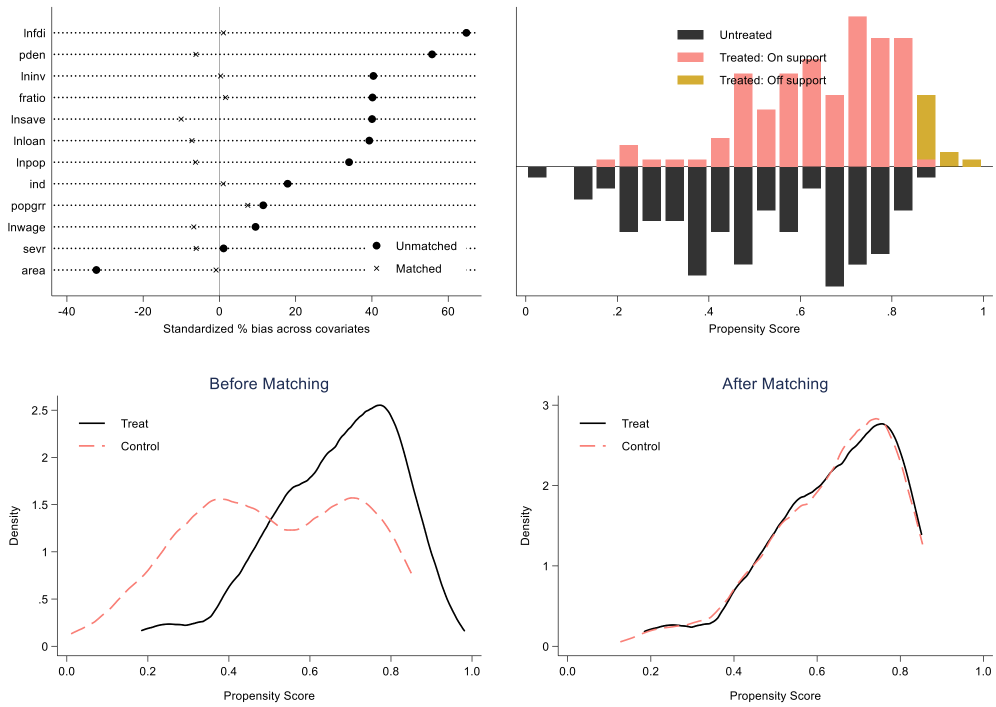

Figure 3. The result of the matching.

4.3. The Parallel Trend

To have a careful discussion, we will compare pretreatment trends and check the impact dynamics using the MV2012 and the event study mentioned above. Firstly, we provide a regression that allows β to vary along the years based on Equation (2) and plot the result in Figure 4. Then, referring to Moser and Voena (2009), the test comparing HSR and non-HSR cities reveals no systematic differences in the pre-trends since they have similar confidence intervals for each time point.

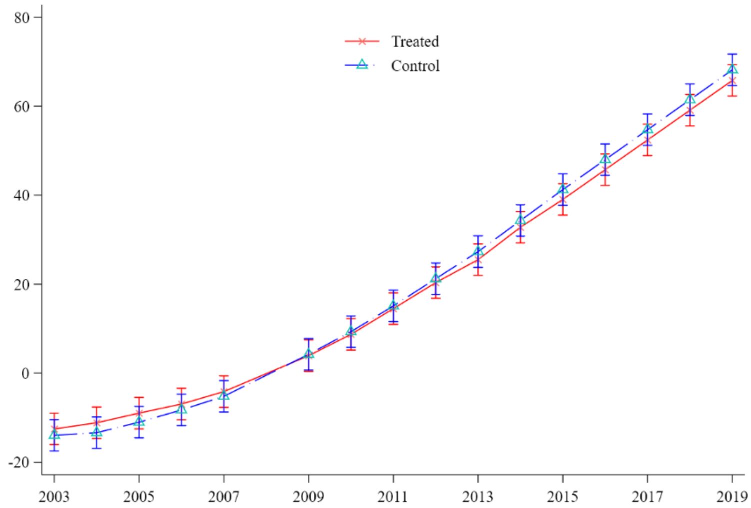

Figure 4. The result of the MV2012 method.

Secondly, the event study based on Equation (3) is estimated and plotted. Figure 5 shows the coefficients and respective 95% confidence intervals. On the one hand, Equation (3) is used to test the parallel trend hypothesis. On the other hand, it can also reflect the dynamic of the treatment effect of HSR on consumption. On the one hand, coefficients before $\tau = 0$ are nonsignificant, confirming the parallel trend hypothesis. In addition, when the effects are allowed to differ over time, we can observe an increase in HSR's treatment effect since the year having HSR in operation, so when we treat the HSR as having the same and average effect, the estimation may give a mixed effect. So in the next section, a heterogeneity test is carried out based on subclasses of cities, and we will further allow the treatment effects of HSR to vary over time.

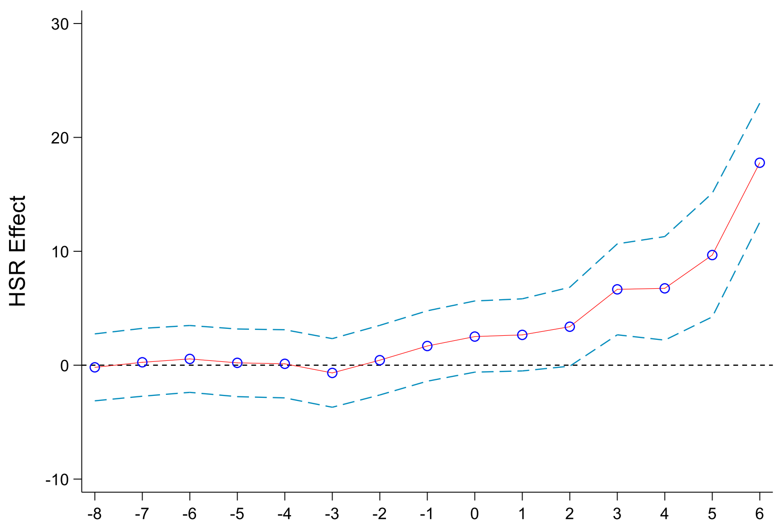

Figure 5. The result of the event study.

4.4. Heterogeneity

Apply the generalized DID method to matched data in Section 4.2, and we get the PSM-DID estimator. Table 3 presents the results. The coefficients of HSR × Post tell us that there seemingly has no significance in the treatment effect of HSR on consumption and are relatively smaller than those in Table 2. However, they are positive and have a coefficient of 0.933, statistically nonsignificant. The results are robust since the values and significances of the coefficients for each control variable are relatively close to the results in Table 2 when considering the control variables. Does that mean HSR has no impact on consumption? To have a careful discussion, we further have a heterogeneity estimation according to the subclasses of cities in China, that is, to have estimations based on cities belonging to subclass 3 to 5 according to the LCC mentioned above.

The results based on subclass cities show that although one of them is nonsignificant, they are all negative. It is fascinating to compare the subclass case to the base model in column (1) of Table 3. For cities in subclass 3, the effect of HSR on consumption equals -2.99 but nonsignificant; for cities in subclass 4 and subclass 5, results indicate that the operation of HSR may reduce the city's consumption by 2.93 and 1.82 billion Yuan, respectively, and the effects are significant in statistical. Compared with the positive coefficients in column (1), the performance of the results is somewhat confusing. We think there is a statistical Simpson paradox on the HSR-consumption nexus. In order to intuitively see the performance of the effects, we calculated the marginal effect of the models in Table 3 and displayed them in Figure 6. As shown, a positive change in margins is associated with three negative changes in different subclasses, which can be seen as evidence of the Simpson paradox. It is not confusing but often overlooked because different cities are on different levels of development, causing HSR's margin effects to be at different locations and weights. Therefore, result drawn from mixed regressions is most often confused. This finding has specific guiding significance for future research, especially in the research related to China's HSR, since cities are so different from each other at the development level.

Table 3. HSR operation and city consumption: PSM-DID and heterogeneity.

	(1)	(2)	(3)	(4)
VARIABLES	PSM-DID	subclass 3	subclass 4	subclass 5
HSR × Post	0.93	-2.99	-2.93***	-1.82**
	(0.957)	(2.076)	(0.887)	(0.776)
ind	-5.08***	-10.32***	-2.69***	-0.43
	(0.822)	(3.039)	(0.822)	(0.488)
indsq	0.03***	0.06***	0.02***	0.00
	(0.006)	(0.019)	(0.005)	(0.003)
lnpop	38.88***	14.63	84.21***	5.26
	(7.610)	(15.876)	(9.643)	(4.644)
lnwage	3.74**	49.52***	7.76***	-0.09
	(1.481)	(7.687)	(2.977)	(0.617)
lninv	-6.48***	-6.41**	-4.61***	-0.71
	(1.063)	(2.716)	(0.987)	(0.758)
lnsave	-6.22***	-0.54	4.19*	-6.44***
	(2.287)	(4.361)	(2.526)	(1.973)
lnloan	-3.37**	-12.01***	-9.33***	-0.73
	(1.353)	(3.475)	(1.482)	(0.824)
fratio	0.16***	0.22***	-0.05	0.09***
	(0.037)	(0.075)	(0.035)	(0.031)
lnfdi	-1.44***	-1.16	0.15	0.28*
	(0.283)	(0.928)	(0.323)	(0.148)
Constant	206.26***	204.07	-337.65***	108.80***
	(61.176)	(179.511)	(73.403)	(36.418)
City FE	YES	YES	YES	YES

Year FE	YES	YES	YES	YES
Observations	3,723	1020	1,394	1,309
R-squared	0.848	0.874	0.921	0.856

*Notes: Standard errors are in parentheses; *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.*

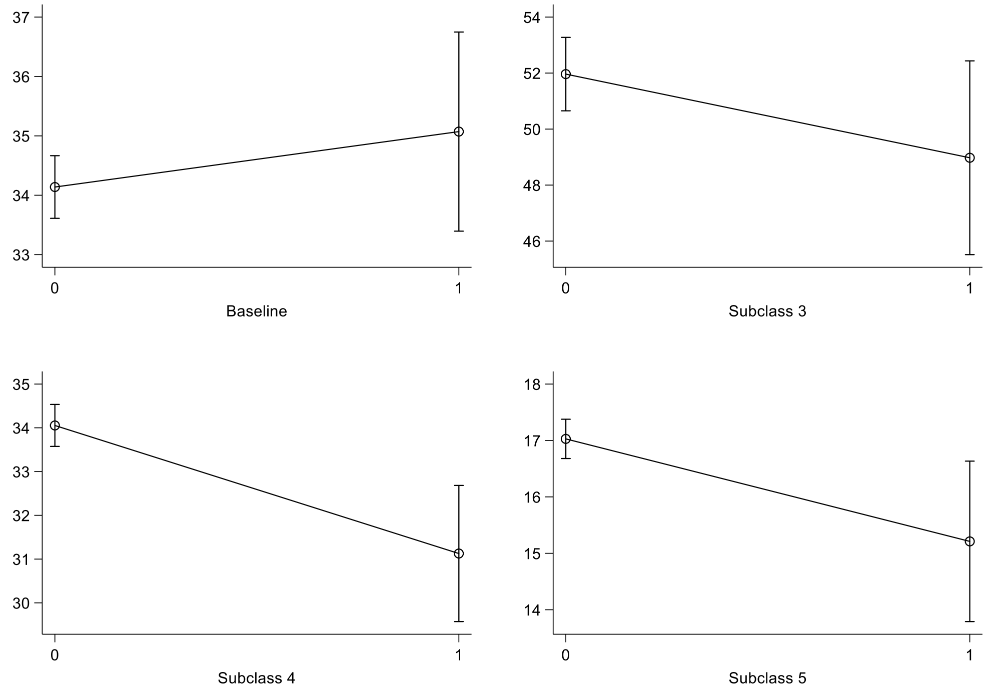

Figure 6. Evidence of a Simpson's paradox.

Furthermore, to allow the treatment effects of HSR to vary over time, we introduce a new time variable indicating the age of a city since the first year of HSR operation. Then, we put the interaction terms of each age year and HSR × Post into the estimation. The results are plotted in Figure 7, where the baseline stands for the results of all minor cities, compared with the regression results of subclasses. For most time points, we can obtain coefficients negative around the zero line for cities in each subclass. In contrast, when we run the regression mixing all subclasses, we observe an increasing series trend in series coefficients. It provides evidence of aspects of the time series.

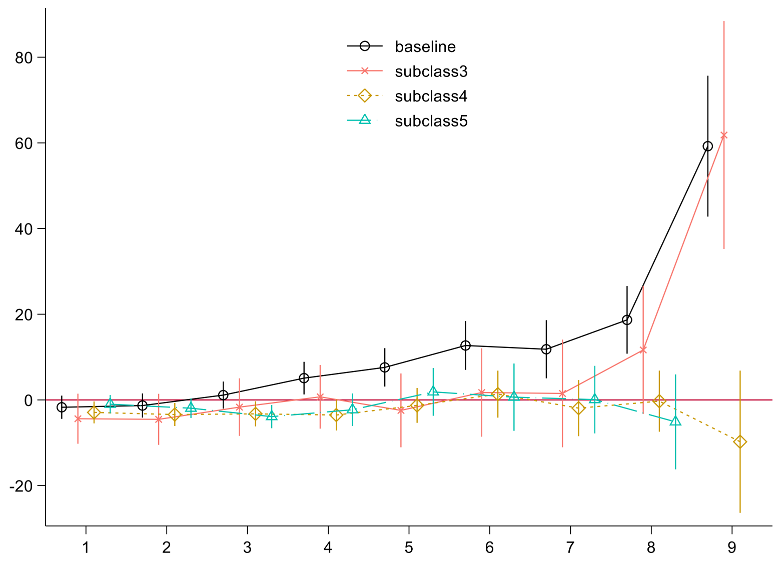

Figure 7. Heterogeneity of the treatment effects over time.

4.5. Dose-Response Assessment

As mentioned above, cities may not randomize across the treated group and control group. At the same time, it is oversimplified to measure the treatment by identifying if there is HSR in operation in cities; the information about HSR development level has been ignored. This paper uses a dose-response model (DR) to correct both bidirectional causality and sample selection bias, this model applies when treatment is continuous, and the selection into treatment may be endogenous. In other words, we relax the assumption that all cities with HSR share the same treatment effect and believe that the treatment effect may vary as the HSR lines/stations increase, so we treat the variable HLS as the dose. Figure 8 shows the results of the DR assessment dealing with endogenous. This paper uses two instrumental variables (IVs): the dummy variable indicating a city on the backbone lines of the Medium and Long-term Railway Network Plan 2004 and the differenced number of railway stations, and the dummy variable of whether a city had a railway in 1961. Those IVs are selected by referring to Faber (2014) and Zheng and Kahn (2013).

Figure 8 gives the baseline model's standardized dose-response functions (DRF) and three subclasses. Here we set the response polynomial in the cubic form to capture the nonlinearity in the treatment effect. Graphs in Figure 8 conclude that there are apparent s-shaped response functions of HSR development on the scale of consumption. For all sampled cities, the treatment effect will first decrease, then increase, and finally decrease with the development of HSR. Cities grouped in subclass 3 have a similar DR function. While cities grouped in subclass 4 and subclass 5 have a mirrored s-shape, with a relatively positive response function compared to cities in subclass 3.

Furthermore, the derivative helps us to find the positions of inflection points of the DRF when the derivative equals zero. The two inflection points appear at the 20 percentile and 60 percentile for all sampled cities and cities belonging to subclass 3, 15 percentile, and 40 percentile for cities belonging to subclass 4 and subclass 5, respectively. In a word, under the control of two-way causality and sample selection bias, HSR has a heterogeneous impact on urban consumption.

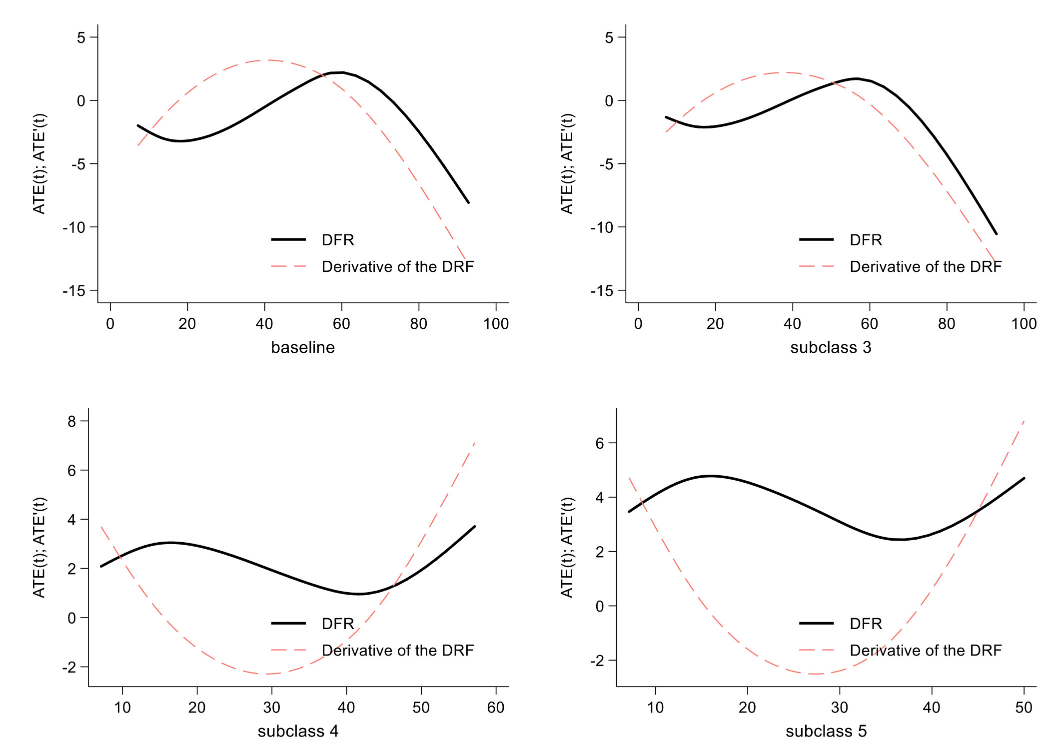

Figure 8. The standardized DRF of HSR on consumption.

4.6. Robustness Check

Table 4 reports the results of robustness checks. The robustness regression is based on the following strategies: (a) a placebo regression takes the assumption that the operation of HSR three years in advance, column (1); (b) previously, we mixed all small cities to run the matching program, to have a robustness check, we rerun the matching using cities within subclasses, the corresponding regressions a listed in column (2) to column (5); (c) considering the potential endogenous issue of HSR, we provided the results of 2SLS with instrument variables, in column (6) to column (9). Results show that the placebo test gives a nonsignificant coefficient of the fake policy intervention, indicating that our analysis is robust. The new PSM way gives similar results to Table 3 but is slightly less significant for subclass 5. When we apply the 2SLS regressions, they are also robust and consistent with the previous estimations. Moreover, the coefficient of HSR × Post in column (6) is significantly positive, strengthening our judgment of the existence of Simpson's paradox. All in all, the results are statistically robust to some extent.

Table 4. Robustness Checks.

	Placebo	Matching within subclasses				IV regressions (2SLS)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	P3	baseline	subclass 3	subclass 4	subclass 5	baseline	subclass 3	subclass 4	subclass 5
HSR × Post	-1.39	0.23	-3.02	-2.07**	-0.62	2.12**	-1.41	-1.99**	-1.47*
	(0.929)	(0.838)	(2.105)	(0.927)	(0.734)	(0.939)	(2.018)	(0.873)	(0.797)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,114	3,536	1,122	1,139	1,275	3,452	947	1,293	1,212
R-squared	0.855	0.848	0.868	0.918	0.861	0.082	0.124	0.199	0.041

Notes: Control variables are included but did not show them here for brevity; P3 in column (1) means a placebo test assuming the intervention happened three years in advance.

5. Conclusion

The HSR has been a calling card of China. Therefore, evaluating the impact of HSR is of great significance for balancing regional economy and promoting sustainable development, and is of implications for other countries because many similar projects in other countries have been constructed. Moreover, HSR can impact various economic and social activities across regions since HSR facilitates cross-city integration. In this paper, we analyzed the treatment effect of HSR in 2003-2019 on city expansion of consumption based on a city-level dataset of China.

Evaluating the treatment effects of HSR was proven difficult but meaningful (Long et al., 2018). after a series of careful estimates and tests, the following findings are drawn: (a) operation of HSR seems to have an overall positive impact on city consumption, but with some doubt on the suitability of candidate control group cities for the DID framework; (b) to improve the estimations, we reevaluated the models with cities in subclasses and with the PSM-DID model, heterogeneity is apparent, and we have found a Simpson's paradox in the relationship of HSR and consumption, that is, an overall positive effect is accompanied by three adverse effects within subclasses; (c) visible s-shaped (or mirrored s-shape) DRFs have been found, it indicates that the treatment effect may vary along the development of HSR. Therefore, it will be meaningful to consider the differences in the city's HSR endowment in future research or practices. Additionally, some checks have been carried out, and the robustness of the analysis is proven.

Generally, we expect HSR to impact economic development and consumption positively. However, will cities get it? There may be some skepticism in the short run. Relying on the growth of the consumption sector to drive economic growth and maintain sustainability is one of the government's expectations. HSR has shown some evidence in stimulating economic activities such as the increase of accessibility, the integration of regions, and the migration of population, referring to previous studies. So follow-up studies and further confirmation are still needed on the HSR-consumption nexus.

One of the most innovative features of this paper is that we provide a much more detailed structural analysis of the topic and lead a study to see the inner structure of the treatment effect of HSR, emphasizing the disparity of cities belonging to different subclasses. The findings have a firm policy and research implications. Governments should consider the varying consumption responses of cities when evaluating the effects of HSR and should watch out for possible Simpson paradox phenomena. Furthermore, several studies argued that disparities between cities had been enlarged by the HSR system (Yin et al., 2015). Therefore, the government should appropriately focus on reshaping the spatial consumption structure and significantly should pivot to peripheral cities to achieve the balanced development of regions. For small cities, having the HSR stations located in the central functional area may gain more benefits.

Moreover, domestic demand from HSR is believed as a vital explosion point for future consumption growth. Many studies have found that the aggregation effect outweighs the radiation effect of HSR in current days; this is not good news to some extent. However, on the other hand, HSR has made cities cooperate and act as city agglomerations, so there is an impetus for balanced development. Therefore, the HSR may produce more indirect benefits in the long run and contribute to the economy's sustainability, and we look forward to that.

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Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

Author contributions

Conceptualization: Xinshuo Hou; Data curation: Dongyang Li, Jianghuan Peng; Methodology: Dongyang Li, Xinshuo Hou; Supervision: Xinshuo Hou; Writing – original draft: Jianghuan Peng, Xinshuo Hou; Writing – review & editing: Xinshuo Hou, Dongyang Li.

References

Ahlfeldt, G. M., and Feddersen, A. (2018). From periphery to core: measuring agglomeration effects using high-speed rail. Journal of Economic Geography 18, 355-390. https://doi.org/10.1093/jeg/lbx005

Aker, J., and Mbiti, I. (2010). Mobile Phones and Economic Development in Africa. Journal of Economic Perspectives 24, 207-232. https://doi.org/10.1257/jep.24.3.207

Albalate, D., Campos, J., and Jiménez, J. (2017). Tourism and high speed rail in Spain: Does the AVE increase local visitors? Annals of Tourism Research 65, 71-82. https://doi.org/10.1016/j.annals.2017.05.004
Albalate, D., and Fageda, X. (2016). High speed rail and tourism: Empirical evidence from Spain. Transportation Research Part A: Policy and Practice 85, 174-185. https://doi.org/10.1016/j.tra.2016.01.009
Almond, D., Li, H., and Zhang, S. (2018). Land Reform and Sex Selection in China. Journal of Political Economy 127. https://doi.org/10.1086/701030
Andrade, J. S., and Duarte, A. P. (2016). Crowding-in and crowding-out effects of public investments in the Portuguese economy. International Review of Applied Economics 30, 488-506. https://doi.org/10.1080/02692171.2015.1122746
Autor, D. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. Journal of Labor Economics 21, 1-42. https://doi.org/10.1086/344122
Balisacan, A., and Pernia, E. (2002). The Rural Road to Poverty Reduction: Some Lessons from the Philippine Experience. Journal of Asian and African Studies - J ASIAN AFR STUD 37, 147-167. https://doi.org/10.1177/002190960203700207
Blundell, R., and Dias, M. (2009). Alternative Approaches to Evaluation in Empirical Microeconomics. Journal of Human Resources 44, 565-640. https://doi.org/10.1353/jhr.2009.0009
Bosker, M., Deichmann, U., and Roberts, M. (2018). Hukou and highways the impact of China's spatial development policies on urbanization and regional inequality. Regional Science and Urban Economics 71, 91-109. https://doi.org/10.1016/j.regsciurbeco.2018.05.007
Cao, W., Feng, X., and Zhang, H. (2019). The structural and spatial properties of the high-speed railway network in China: A complex network perspective. Journal of Rail Transport Planning & Management 9, 46-56. https://doi.org/10.1016/j.jrtpm.2018.10.001
Card, D., and Krueger, A. B. (2000). Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania: Reply. American Economic Review 90, 1397-1420. https://doi.org/10.1257/aer.90.5.1397
Chen, B., and Yao, Y. (2011). The Cursed Virtue: Government Infrastructural Investment and Household Consumption in Chinese Provinces* [https://doi.org/10.1111/j.1468-0084.2011.00678.x]. Oxford Bulletin of Economics and Statistics 73, 856-877. https://doi.org/10.1111/j.1468-0084.2011.00678.x
D'Acunto, F., Hoang, D., and Weber, M. (2017). The Effect of Unconventional Fiscal Policy on Consumption Expenditure. SSRN Electronic Journal 15, 1-83. https://doi.org/10.2139/ssrn.2826084
Dawood, T. C., and Francois, J. N. (2018). Substitution between private and government consumption in African economies. Economic Modelling 73, 129-139. https://doi.org/10.1016/j.econmod.2018.03.012
Diao, M. (2018). Does growth follow the rail? The potential impact of high-speed rail on the economic geography of China. Transportation Research Part A: Policy and Practice 113, 279-290. https://doi.org/10.1016/j.tra.2018.04.024
Donaldson, D. (2018). Railroads of the Raj: Estimating the Impact of Transportation Infrastructure. American Economic Review 108, 899-934. https://doi.org/10.1257/aer.20101199
Donaldson, D., and Hornbeck, R. (2016). Railroads and American Economic Growth: A "Market Access" Approach *. The Quarterly Journal of Economics 131, 799-858. https://doi.org/10.1093/qje/qjw002
Dong, X. (2018). High-speed railway and urban sectoral employment in China. Transportation Research Part A: Policy and Practice 116, 603-621. https://doi.org/10.1016/j.tra.2018.07.010
Dong, X., Zheng, S., and Kahn, M. (2019). The Role of Transportation Speed in Facilitating High Skilled Teamwork Across Cities. Journal of Urban Economics 115, 103212. https://doi.org/10.1016/j.jue.2019.103212
Ercolani, V., and Valle e Azevedo, J. (2014). The effects of public spending externalities. Journal of Economic Dynamics and Control 46, 173-199. https://doi.org/10.1016/j.jedc.2014.06.016
Faber, B. (2014). Trade Integration, Market Size, and Industrialization: Evidence from China's National Trunk Highway System. The Review of Economic Studies 81, 1046-1070. https://doi.org/10.1093/restud/rdu010
Funashima, Y., and Ohtsuka, Y. (2019). Spatial crowding-out and crowding-in effects of government spending on the private sector in Japan. Regional Science and Urban Economics 75, 35-48. https://doi.org/10.1016/j.regsciurbeco.2019.01.008
Geng, B., Bao, H., and Liang, Y. (2015). A study of the effect of a high-speed rail station on spatial variations in housing price based on the hedonic model. Habitat International 49, 333-339. https://doi.org/10.1016/j.habitatint.2015.06.005
Gibson, J., and Rozelle, S. (2003). Poverty and Access to Roads in Papua New Guinea. Economic development and cultural change 52, 159-185. https://doi.org/10.1086/380424

Heutel, G. (2012). Crowding Out and Crowding In of Private Donations and Government Grants. Public Finance Review 42, 143-175. https://doi.org/10.1177/1091142112447525

Hirano, K., and Imbens, G. (2005). The Propensity Score with Continuous Treatments (Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives: An Essential Journey with Donald Rubin's Statistical Family (pp. 73-84). Wiley Series in Probability and Statistics. https://doi.org/10.1002/0470090456.ch7

Jiang, X., He, X., Zhang, L., Qin, H., and Shao, F. (2017). Multimodal transportation infrastructure investment and regional economic development: A structural equation modeling empirical analysis in China from 1986 to 2011. Transport Policy 54, 43-52. https://doi.org/10.1016/j.tranpol.2016.11.004

Ke, X., Chen, H., Hong, Y., and Hsiao, C. (2017). Do China's high-speed-rail projects promote local economy?—New evidence from a panel data approach. China Economic Review 44, 203-226. https://doi.org/10.1016/j.chieco.2017.02.008

Kudamatsu, M. (2012). Has Democratization Reduced Infant Mortality in Sub-Saharan Africa? Evidence from Micro Data. Journal of the European Economic Association 10, 1294-1317. https://doi.org/10.1111/j.1542-4774.2012.01092.x

Lewis, V., and Winkler, R. (2017). Government Spending, Entry, and The Consumption Crowding-In Puzzle [https://doi.org/10.1111/iere.12241]. International Economic Review 58, 943-972. https://doi.org/10.1111/iere.12241

Li, H., Strauss, J., Shunxiang, H., and Lui, L. (2018). Do high-speed railways lead to urban economic growth in China? A panel data study of China’s cities. The Quarterly Review of Economics and Finance 69, 70-89. https://doi.org/10.1016/j.qref.2018.04.002

Long, F., Zheng, L., and Song, Z. (2018). High-speed rail and urban expansion: An empirical study using a time series of nighttime light satellite data in China. Journal of Transport Geography 72, 106-118. https://doi.org/10.1016/j.jtrangeo.2018.08.011

Meng, X., Lin, S., and Zhu, X. (2018). The resource redistribution effect of high-speed rail stations on the economic growth of neighbouring regions: Evidence from China. Transport Policy 68, 178-191. https://doi.org/10.1016/j.tranpol.2018.05.006

Moser, P., and Voena, A. (2009). Compulsory Licensing: Evidence from the Trading with the Enemy Act. American Economic Review 102, 396-427. https://doi.org/10.2139/ssrn.1313867

Mu, R., de Jong, M., Ma, Y., and Xi, B. (2015). Trading off public values in High-Speed Rail development in China. Journal of Transport Geography 43, 66-77. https://doi.org/10.1016/j.jtrangeo.2015.01.010

Pagliara, F., Mauriello, F., and Garofalo, A. (2017). Exploring the interdependences between High Speed Rail systems and tourism: Some evidence from Italy. Transportation Research Part A: Policy and Practice 106, 300-308. https://doi.org/10.1016/j.tra.2017.09.022

Pereira, A. M., and Andraz, J. M. (2004). Public highway spending and state spillovers in the USA. Applied Economics Letters 11, 785-788. https://doi.org/10.1080/1350485042000254593

Qin, Y. (2017). ‘No county left behind?’ The distributional impact of high-speed rail upgrades in China. Journal of Economic Geography 17, 489-520. https://doi.org/10.1093/jeg/lbw013

Reinhart, C. M., Reinhart, V., and Tashiro, T. (2016). Does Reserve Accumulation Crowd Out Investment? Journal of International Money and Finance 63, 89-111. https://doi.org/10.1016/j.jimonfin.2015.11.004

Shao, S., Tian, Z., and Yang, L. (2017). High speed rail and urban service industry agglomeration: Evidence from China's Yangtze River Delta region. Journal of Transport Geography 64, 174-183. https://doi.org/10.1016/j.jtrangeo.2017.08.019

Turnovsky, S., and Monteiro, G. (2007). Consumption Externalities, Production Externalities, and Efficient Capital Accumulation Under Time Non-Separable Preferences. European Economic Review 51, 479-504. https://doi.org/10.1016/j.euroecorev.2005.12.001

Xu, W., Zhou, J., Yang, L., and Li, L. (2018). The implications of high-speed rail for Chinese cities: Connectivity and accessibility. Transportation Research Part A: Policy and Practice 116, 308-326. https://doi.org/10.1016/j.tra.2018.06.023

Yin, M., Bertolini, L., and Duan, J. (2015). The effects of the high-speed railway on urban development: International experience and potential implications for China. Progress in Planning 98, 1-52. https://doi.org/10.1016/j.progress.2013.11.001

Zhang, H., and Meng, X. (2021). The crowding out channel: Housing boom and investment in China. Finance Research Letters 43, 101959. https://doi.org/10.1016/j.frl.2021.101959

Zhang, Y., Wang, X., and Chen, K. (2013). Growth and Distributive Effects of Public Infrastructure Investments in China. In J. Cockburn, Y. Dissou, J.-Y. Duclos, and L. Tiberti (Eds.), Infrastructure and Economic Growth in Asia (pp. 87-116). Springer International Publishing. https://doi.org/10.1007/978-3-319-03137-8_4

Zheng, S., and Kahn, M. (2013). China's bullet trains facilitate market integration and mitigate the cost of mega-city growth. Proceedings of the National Academy of Sciences of the United States of America 110, 1248-1253. https://doi.org/10.1073/pnas.1209247110

Zhu, Y., Diao, M., and Fu, G. (2016). The evolution of accessibility surface of China in the high-speed-rail era. Environment and Planning A: Economy and Space 48, 2108-2111. https://doi.org/10.1177/0308518X15619935