Do China's High-Speed-Rail Projects Promote Local Economy?
---New evidence from a panel data approach

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Abstract: This paper evaluates the effect of High Speed Rail (HSR) projects on the economic growth of targeted city nodes (HSR cities) in China using prefectural-level city data from 1990 to 2013. Employing a panel data program evaluation method devised by Hsiao, Chin and Wan (2012), we construct hypothetical counterfactuals for per capita real GDP of HSR cities in the absence of their respective HSR projects using the outcomes in selected non-HSR cities. We find that the responses to HSR treatment are heterogeneous with regard to location, route, and region. The location-level impact ranges between 5% and 59% and is not temporary. HSR cities with positive effects concentrate along the Hu-Ning Segment, the Yong-Tai-Wen-Fu-Xia Segment, and within the Hunan province along the Wu-Guang HSR. These cities are mainly located in the eastern coastal regions of China, in core urban agglomeration regions that allow them to be transportation hubs. In general, the gain for local economies is greater for cities that are more industrialized, with more ability of the service sector to absorb enough labor, and with better supporting infrastructure. On the other hand, local protectionism hampers the development of HSR cities. We also show that at different project stages, HSR cities experience different gains.

JEL classification: C23, C51, C54, O18, R11

Keywords: counterfactual, economic growth, infrastructure, High-Speed-Rail, location-level heterogeneity, panel data, program evaluation, transportation

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1. Introduction

Rail transport is a crucial mode of inter-region transportation in China, a large developing country with widespread geographical distribution of natural resources and population. As a result, High Speed Rail (HSR) networks in China have expanded drastically over the past decade. In 2008, the first HSR line, Beijing-Tianjin Intercity HSR[1] opened, following which the country embarked on a HSR construction boom. From 2011 to 2015, the Twelfth Five-Year Plan, HSR investment was around 1.875 trillion RMB (275 billion USD) (China Railway Corporation, 2016). The State Council, in its revised Mid-to-Long Term Railway Development Plan (2008), stated that the aim of this HSR grid was to form connections between provincial capitals and other widely spaced major cities with diverse natural resources and social-economic structures.[2] The Plan set the goal of expanding railroad operation mileages to 120,000 kilometers using a planned investment of 2.047 trillion RMB (300 billion USD) by the end of 2020 (Lin, 2014). The so-called Four Vertical and Four Horizontal HSR framework—composed of four north-south corridors, Jing-hu, Jing-Guang-Shen-HK, Jing-Ha, and Hang-Fu-Shen,[3] and four east-west corridors, Xu-Lan, Hu-Kun, Qing-Tai and Hu-Han-Rong HSRs (State Council, 2008; see Fig.1)—constitutes the arterial HSR corridors of China and opened to public in 2015.

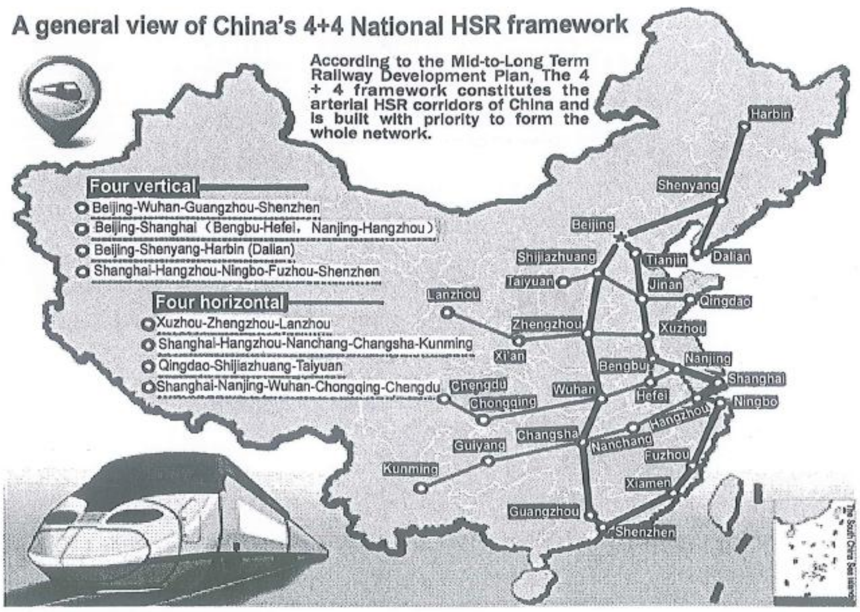

Fig. 1. A general view of China's 4+4 national HSR framework. Notes: The data source is from the Ministry of Railways of the People's Republic of China. The map is by Zhe Lu of Xinhua News Agency and translated into English by the author. The bold lines represent the four vertical HSR lines and the fine lines represent the four horizontal HSR lines.

HSR construction has raised heated debates worldwide, and the empirical results are very

[1] Intercity HSR lines aim to connect specific metropolitan areas, often within a relatively short distance, i.e., 100-200 kilometers. Usually, Intercity HSR lines can reach a speed of 350km/hour.

[2] The former Ministry of Railways in China stated that, in general, the design of HSR lines and route placement should be based on a comprehensive consideration of economic development, population, resource distribution, land development, national defense, economic security, social stability and balanced regional development (State Council, 2008). For a specific route placement, the China Railway Survey and Design Group in charge of engineering design will take into account of other crucial factors, e.g. topographical and geomorphologic characteristics, proper distances between stations, nodal point and fierce competition from local governments to advocate route passing through their region as well.

[3] It is also named the Southeast coast HSR line.

mixed (e.g. Ahlfeldt & Feddersen, 2010; Marti-Hennenberg, 2000; Sasaki et al., 1997; Vickerman & Ulied, 2006). For China, Zheng & Kahn (2012) investigated the HSR effect on city development in terms of real estate prices, using both the 1961 historical railway network and the deployed troops dummy as IVs. They find that HSR connection boosts housing prices in secondary cities close to megacities. Lin (2014) primarily applied the difference-in-difference (DID) method to a restricted sample of HSR treatment cities and found a large connection effect on industrial and service employment for connected prefectural-cities but no effect on GDP or population growth. Li (2000) used simulation to evaluate the Jing-Hu HSR line in China and projected that the aggregate GDP of treated provinces along the line would decrease temporarily before starting to increase five years after operation began. In this paper, we use China's city data from 1990 to 2013 to investigate the heterogeneous impact of HSR projects at the local level. We are primarily interested in whether large-scale HSR construction projects in China benefit local economic growth for the targeted city nodes in which they were located (subsequently "HSR cities"). If so, do all HSR cities gain uniformly? If not, what kind of location is more likely to gain or lose due to HSR?

One of the main difficulties estimating the impact of HSR projects on local economic development for targeted city nodes is constructing the appropriate counterfactual in the absence of the transportation improvement (Redding et al., 2015). Observed data could be subject to the so-called "selection on observables and unobservables" (e.g. Rosenbaum & Rubin, 1983; Heckman & Vytlacil, 2001). Based on inter/intra-city regression, studies have developed compelling identification strategies to address the problem of endogenous route placement. The most widely used is Instrumental Variables (IV) strategies (e.g. Baum-Snow, 2007; Duranton & Turner, 2012; Chandra & Thompson, 2000; Faber, 2014; Banerjee et al., 2012; Baum-Snow et al., 2015a; Baum-Snow et al., 2015b). Other complementary approaches include natural experiment, the Regression Discontinuity Design (RDD) approach, and the Propensity Score Matching (PSM) method (e.g. Donaldson, 2015; Casaburi et al., 2013; van de Walle & Mu, 2007). The aforementioned approaches e.g. DID, PSM, and RDD essentially assume no selection on unobservables (conditional on certain observed variables). However, local leadership, social capital, and endowment can also play an important role in the selection of specific routing but are either difficult to measure or unobservable. Proxies for important determinants for both route placement and the resulting outcome are needed but are difficult to find (van de Walle, 2009). Moreover, quasi-experimental design restricts transportation studies to inconsequential regions, e.g., nontargeted peripheral regions or intermediated stops (Redding et al., 2015). Furthermore, the underlying behavioral assumption of the conventional IV-2SLS method is the homogeneous response of each individual unit (Heckman, 1997), which could very likely contradict with one of the key stylized facts that locations are heterogeneous (Behrens & Robert-Nicoud, 2015). [4]

Our study uses a panel data evaluation method recently developed by Hsiao, Ching, and Wan (2012) to construct the counterfactuals of per capita real GDP of HSR cities in the absence of HSR projects. The basic method of constructing counterfactual outcomes relies on correlations among

[4] Locations differ in endowments (natural resources, constructible area, soil quality, etc.), accessibility (access to navigable river, natural harbors, relative location in the urban system, etc.), and many other first- and second-nature characteristics (climate, consumption and production amenities, geological and climatic hazards, etc.). Moreover, Behrens & Robert-Nicoud (2015) summarized that empirical work on city sizes and productivity suggests that these locational fundamentals explain about one-fifth of the observed geographical concentration and pin down city locations to explain why those locations and city sizes are fairly resilient to large shocks or technological change (Ellison & Glaeser, 1999; Bleakley & Lin, 2012).

cross-sectional units—cities in our case. Those cross-sectional correlations are attributed to the presence of a few latent common factors that explain the bulk of variations in city-level outcomes. The Hsiao et al. (2012) method is a "measurement without theory" approach to model city-level economic outcomes instead of a reduced-form inter/intra-city regression approach (Ching et al., 2012). The method avoids selection bias due to selection on observables and unobservables. More importantly, Hsiao et al. (2012)'s method is not sensitive to assumptions about how individual units process information, in contrast to the conventional application of IV methods (Heckman, 1997). It allows us to fully capture city-level heterogeneity and characterize the spatial distribution of the local gains across HSR cities at route and regional level.

We find suggestive evidence that the impacts of HSR treatment vary in terms of city location, route, and region for the cities we studied, with significant and diverse impacts on per capita GDP. Targeted cities with positive impacts are mostly located in coastal regions, concentrated in core urban agglomeration regions, and transportation hubs. Our estimates indicate that the gain on the local economy is greater for cities that are more industrialized, with more ability of the service sector to absorb labor, and with better supporting infrastructure. During construction and early operation phases, different types of HSR cities tend to show different benefits. Together these findings provide strong econometric evidence in support of the arguments that HSR treatment are heterogeneous at location level. Understanding how HSR projects affect individual targeted city nodes differently and what type of locations are more likely to show gains or losses is very useful for formulating regional development policies.

The rest of the paper is organized as follows: section 2 describes the methodological framework of Hsiao et al. (2012). Section 3 describes data and key settings required to implement the method. Section 4 gives estimates of the treatment effects for each HSR city along the studied HSR Lines/Segments. Section 5 contains additional analysis to explain heterogeneous HSR effects. Section 6 reports our robustness checks on the baseline treatment effects. Section 7 contains our concluding remarks.

2. The model and estimation

In this section, we briefly summarize the panel data evaluation method of Hsiao et al. (2012). Let (y_{it}^1, y_{it}^0) denote the potential outcomes of the i th city's per capita real GDP in year t with and without the HSR project intervention, respectively. Then, the HSR effect on the per capita real GDP at time t is simply

$$\Delta_{1t} = y_{1t}^1 - y_{1t}^0 \tag{1}$$

However, we do not simultaneously observe y_{it}^0 and y_{it}^1. The observed data typically takes the form of (y_{it}, d_{it}),

$$y_{it} = d_{it} y_{it}^1 + (1 - d_{it}) y_{it}^0 \tag{2}$$

where $d_{it} = 1$ if the i th city receives the HSR treatment and $d_{it} = 0$ otherwise.

We consider the case of no treatment to y_{it} for all i and for $t = 1, ..., T_1$. For $t = T_1 + 1, ..., T$, there is one city, supposing that the first city without loss of generality, receives a HSR treatment but all other y_{it}, $j = 2, ..., N$ in the control group do not receive any HSR treatment.

The problem in estimating (1) is that there is missing data in y_{1t}^{0} . To construct the counterfactual outcome, most of the existing literature relies on inter/intra-city regression or a variant of it. However, a reduced-form model usually suffers from omitted variable bias to which the selection bias belongs (e.g. Heckman, 1979). Moreover, the average treatment effects estimated by the IV-2SLS potentially mask treatment effect heterogeneity across different types of cities (Baum-Snow et al., 2015a).

To address this problem, we apply the methodology of Hsiao et al. (2012). We assume a common factors structure in the panel data of city outcomes, utilizing the information in non-HSR cities to predict what would have happened had the HSR projects not been implemented. Specially, we assume we can decompose the per capita real GDP of each city into two components: the first is the impact of K common factors, f_t, that drives per capita real GDP of all cities to change over time, including both HSR cities and non-HSR cities. These factors can be national macro policies, international political and economical shocks, trade development, technological progress, etc. The second is the idiosyncratic component $\alpha_i + u_{it}$, where α_i represents the fixed city-specific effect and u_{it} represents the idiosyncratic error with $E(u_{it}) = 0$ and uncorrelated with u_{jt} for $j \neq i$. Then

$$y_{it} = b_i^{'} f_t + \alpha_i + u_{it}, \; i = 1,...,N, \; t = 1,...,T \tag{3}$$

Where b_i denotes the $K \times 1$ vector of constant loadings that may vary across i . To explain it in another way, each city is affected by common factors f_t, though the response to f_t could differ across cities. In this way, our specified common factor model is less restrictive than the existing reduced-form regression framework, which assumes homogeneous response to the transportation variable across i . More importantly, our factor model is consistent with location heterogeneity in nature.

Let $y_t = (y_{1t},..., y_{Nt})^{'}$ be a $N \times 1$ vector of y_{it} in year t . Since there is no HSR policy intervention before T_1, then the observed y_t takes the form

$$y_t = y_t^0 = \alpha + \mathrm{B} f_t + u_t \quad \text{for} \quad t = 1,..., T_1, \tag{4}$$

where $y_t^0 = (y_{1t}^0,..., y_{Nt}^0)^{'}$, $\alpha = (\alpha_1,...,\alpha_N)^{'}$, $\mathrm{B} = (b_1,...,b_N)^{'}$ is the $N \times K$ factor loading matrix and $u_t = (u_1,...,u_N)^{'}$.

Since at time $T_1 + 1$, namely the cut-off point, the HSR project construction took effect for the first city, from time $T_1 + 1$ on, we have

$$y_{1t} = y_{1t}^1 = \alpha_1 + b_1^{'} f_t + \Delta_{1t} + u_{1t} \quad \text{for} \quad t = T_1 + 1,..., T \; , \tag{5}$$

where Δ_{1t} is the treatment effect capturing the impact of the HSR project on per capita real GDP in city 1 after the implementation of a new HSR line.

As for non-HSR cities that are not affected by the HSR project, for all time horizons, we have

$$y_{it} = y_{it}^0 = \alpha_i + b_i^{'} f_t + u_{it} \quad \text{for} \quad i = 2,..., N \quad \text{and} \quad t = 1,..., T \tag{6}$$

When $N > K$, there exists a vector a satisfying

$$a^{'}\mathrm{B} = 0 \tag{7}$$

Combining Eqs. (3) and (7), the conditional mean of the per capita real GDP of the HSR city given the per capita real GDP of control group candidates is a linear function of control group cities. Then,

$$y_{1t}^{0} = E(y_{1t}^{0} \mid y_{-t}) + \varepsilon_{1t} = \bar{\alpha} + a_{-1}^{*'} y_{-1t} + u_{1t}^{*} \quad (8)$$

where $y_{-t} = (y_{2t}, ..., y_{Nt})'$, $y_t = (y_{1t}, y_{-t}')'$.

As long as Assumption 5 in Hsiao et al., (2012) holds, that is

$$E(u_{is} \mid d_{1t}) = 0 \text{, for } i \neq 1 \quad (9)$$

Hsiao et al. (2012) show that $\bar{\alpha}$ and a_{-1}^{*} can be estimated by minimizing

$$\frac{1}{T_1} \sum_{t=1}^{T_1} (y_{1t}^{0} - \bar{\alpha} - a_{-1}^{*} y_{-1t})' (y_{1t}^{0} - \bar{\alpha} - a_{-1}^{*} y_{-1t}) \quad (10)$$

We can define the predictor for counterfactual y_{1t}^{0} without the HSR project intervention as

$$\hat{y}_{1t}^{0} = \hat{\bar{\alpha}} + \hat{a}_{-1}^{*} y_{-1t} \text{, for } t > T_1 \quad (11)$$

Then, a prediction for the treatment effect due to construction of the HSR project on the HSR-city at time t will be

$$\hat{\Delta}_{1t} = y_{1t}^{1} - \hat{y}_{1t}^{0} \text{, for } t > T_1 \quad (12)$$

The construction of the standard error of $\hat{y}_{1t}^{0}$, $\sigma_{y_{1t}^{0}}$, follows from the standard prediction error formula. Hence, the confidence band for $\hat{\Delta}_{1t}$ is constructed as

$$\hat{\Delta}_{1t} \pm c\sigma_{y_{1t}^{0}} \quad (13)$$

where c is chosen by the desired confidence level (Hsiao, 2014).

If Δ_{1t} is stationary, the average treatment effect (ATE) averaged over the whole policy evaluation period $T_1 + 1$ to T can be consistently estimated by

$$\frac{1}{(T - T_1)} \sum_{t=T_1+1}^{T} \hat{\Delta}_{1t} \quad (14)$$

The next issue is how to choose the best prediction model to construct the counterfactuals. In our case, the sample observations are no more than 20 years. Using all available cities is generally not a feasible choice unless T_1 is large. To balance the within-sample fit with the post-sample prediction accuracy, we use some model selection criteria to choose a subset of cities to construct the counterfactual, e.g., the corrected Akaike Information Criterion (AICC; Hurvich & Tsai, 1989).

3. Data and settings

In this section, we will introduce our data and clarify the settings to properly implement the procedure developed in Hsiao et al. (2012).

3.1 Data

Prefectural-level cities (Dijishi) are our primary unit of study[5]. To apply the Hsiao et al. (2012) methodology, we needed a panel of per capita real GDP across prefectural-level cities including HSR cities and their potential control groups. A prefectural-level city is a city (Shi) and a prefecture (Diqu) that have been merged into one unified jurisdiction. Typically, it is an administrative unit comprising a main central urban area (a city in the usual sense) and its much larger surrounding rural area containing smaller cities, counties, and towns. We choose to study prefectural-level cities because HSR stops in China are usually located in surrounding rural areas close to the central urban area or in outer suburbs. Land expropriation implemented before construction period, infrastructure, station equipment, traction power supply system, bullet trains, etc. implemented during the construction period, and land development during construction and operation periods all concentrate in rural areas.

To calculate per capita real GDP, we used the annual nominal GDP deflated by average population at the end of year and then converted nominal variables into real terms with appropriate price deflators. The prefectural-level nominal GDP is from China City Statistical Yearbook from 1991 to 2014. The missing data were supplemented from Provincial Statistical Year Book provided by the National Bureau of Statistics in China (NBSC) in corresponding years.[6] The prefectural-level population data we used were total population counts between 1989 and 2013, recorded in the China City Statistical Yearbook, 1990-2014. We calculate the mean population by taking the simple average of the total population in two consecutive years. To obtain real terms, we chose to adjust by the provincial CPI consistently reported in the China Statistical Yearbook in 1991-2014[7]. The exact times when construction and operation started and the actual HSR stations were obtained through official documents or news (e.g., the National Railway Administration of the People's Republic of China, 2016).

3.2 Settings

3.2.1 Control group choice

Two criteria needed to be satisfied when selecting cities for the control group. First, a control city must display a strong correlation with a treated city in the outcome variable—per capita real GDP in our case. This can be justified by the large value of R-squared in the pre-intervention regression. Secondly, a control city should be exogenous to the HSR treatment indicated by Eq. (9). This implies that ideally the HSR project should have absolutely no influence on per capita real GDP of control group cities. However, many factors such as migration can cause the outcome variable of control group cities to change. Under this circumstance, adjacent regions of HSR cities

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[5] Municipalities directly under the central government including: Beijing, Shanghai, Tianjin, and Chongqing are treated administratively as provinces rather than prefectural-level city. Thus, they are not considered in our study. For the same reason, subprovincial cities such as Nanjing, Jinan, Guangzhou, Wuhan, Xiamen, Ningbo, etc. are not considered in our study either. In addition, other types of prefectural-level administrative regions e.g. autonomous prefecture (Zizhizhou), prefecture (Diqu) or leagues (Meng) are exclude from our sample because data availability is much poorer in these regions (Baum-Snow et al., 2015a).

[6] Nominal GDP in 1990, 1991 and 1994-2012 is from China City Statistical Yearbook. The GDP data in 1992 and 1993 is not reported in China City Statistical Yearbook, so we supplemented it from the Provincial Statistical Year Book.

[7] The GDP deflator is only available from 1996 for most prefectural-level cities, thus it is too short for in-sample fit.

are most likely to be affected by spillover effects or potential reorganization from HSR cities. Similar to Bai et al. (2014), we chose a control group of prefectural-level cities by excluding all HSR cities that were completed or still under construction and their adjacent non-HSR cities (subsequently “neighbors of HSR cities”) from the pool of all prefectural-level cities in China within the sample period 1990-2013. We used this strict criterion to ensure the key identification Assumption 5 (strict cross-exogeneity) in Hsiao et al. (2012) holds.

Accordingly, we obtained 14 prefectural-level cities satisfying the exogeneity criterion during the sample period 1990-2013: Yancheng, Zhoushan, Tonghua, Yinchuan, Shizuishan, Wuhai, Chifeng, Liupanshui, Hegang, Jinchang, Karamay, Baotou, Hohhot, and Shuangyashan[8]. Most of the 14 cities are from geographically remote regions in China, except Yancheng and Zhoushan. This is fully allowed when applying the method in Hsiao et al. (2012) to construct counterfactuals, because the basic idea is to choose a (best) predictor, instead of finding a control group that is similar in covariates to the treatment group. To obtain better predictions of the counterfactuals, we experimented with different combinations of these 14 cities to find those which generated the best fit for a pre-intervention sample period following the model selection procedure described in Section 4.1.

3.2.2 Treatment group choice

We focused on the Four Vertical HSR lines running north-south, an important part of the national HSR network. To obtain as much data for the policy evaluation period of HSR projects as possible, we investigated the Four Vertical HSR Segments/Lines which was constructed first in a single phase and is already open to public. Accordingly, we chose Jing-Hu HSR and Hu-Ning Intercity HSR, Wu-Guang HSR, and Yong-Tai-Wen-Fu-Xia Segments along the Hang-Fu-Shen HSR. Table 1 tabulates the basic information for the four studied HSR lines/Segments.

Many prefectures and counties experienced changes in administrative status and new prefectural-level cities were established during our sample period, we restricted our treatment group cities to the HSR cities with at least 10 years of pre-intervention observations to obtain enough data. We have 21 HSR cities in our treatment group with basic information in Table 1[9].

For the initial observation at $t = 1$ and the cut-off point $T_1 + 1$, they were set as described in Table 2.

4. The treatment effects of HSR projects

4.1 Predictive Models for the treatment group cities

We constructed the predictives using pretreatment period data and chose the combination from

[8] There could have been other non-HSR cities that satisfied the exogeneity criterion. However, due to inconsistent data, we did not use them.

[9] See Table 1 and 2 for further details.

Table 1: The HSR Lines/Segments and HSR cities in our treatment group

No.	HSR Lines/Segments	Construct start	Operation start	Province	Region	Prefectural-level HSR cities	Operating mileages /km
1	Beijing-Nanjing Segment on Jing-Hu HSR	2008	2011	Hebei Shandong Jiangsu	North East East	Langfang, Cangzhou Taian, Jining Xuzhou	1318
2	Hu-Ning Intercity HSR and Hu-Ning Segment on Jing-Hu HSR	2008	2010 2011	Jiangsu	East	Zhenjiang, Changzhou, Wuxi, Suzhou	301
3	Wu-Guang HSR	2005	2009	Hunan Guangdong	Middle South	Yueyang, Changsha, Zhuzhou, Hengyang Shaoguan, Qingyuan	1068.8
4	Yong-Tai-Wen, Wen-Fu, Fu-Xia Segments on Southeast coastal HSR	2005	2009 2010	Zhejiang Fujian	East	Taizhou, Wenzhou, Ningde Fuzhou, Putian, Quanzhou	855.69

Notes: 1. The four HSR cities on the Hu-Ning Segment along the Jing-Hu HSR Line are also targeted city nodes on the Hu-Ning Intercity HSR. And the construction of both projects initiated in 2008. Thus, the treatment for targeted cities along the Hu-Ning Corridor is actually from both the Hu-Ning Segment on the Jing-Hu HSR and the Hu-Ning Intercity HSR. 2. Prefectural-level HSR cities along the Beijing-Nanjing Segment include Langfang, Cangzhou, Dezhou, Taian, Jining, Zaozhuang, Suzhou, Bengbu, Chuzhou and Xuzhou. The per capita real GDP of Cangzhou, Dezhou, Zaozhuang, Suzhou and Bengbu fluctuate in the pre-treatment periods, due to changes in administrative status (i.e. city-prefectures merged) in 1993, 1998, 2001, and 1998 respectively. Except for Cangzhou, all the other three cities have pre-treatment observations less than 10, thus they are dropped from our treatment group (See the notes of Table 2). Chuzhou was first time treated by the Ning-He (Nanjing-Hefei) HSR in year 2005, thus we drop it from the treatment group of the Jing-Hu HSR Line. 3. Prefectural-level HSR cities on the Wu-Guang Segment include Xianning, Yueyang, Changsha, Zhuzhou, Hengyang, Chenzhou, Shaoguan, and Qingyuan. Due to the same reason of fluctuating per capita GDP, Xianning and Chenzhou are dropped from the treatment group. 4. Data source: National Railway Administration of the People’s Republic of China.

Table 2: Settings used in implementing Hsiao et al. (2012) method

Outcome variable	• Per capita real GDP in log levels (1990-2013, deflated by CPI 1990)
Treatment group units	• 21 prefectural-level HSR cities along the four studied HSR projects (See the notes of Table 1)
Cut-off point	• Set T_1+1 at one year before the year in which the construction started for the four studied HSR projects (See Table 1)
Initial observation	• Set t=1 at year 1990
	• For the costal HSR cities, set t=1 at year 1994; For cities experienced changes in administrative status or new establishment after 1990, set t=1 to be the year after the change or establishment (See the notes of Table 1).
Control group units	• Prefectural-level cities, with per capita real GDP data available and consistent
	• Excluding all HSR cities that have been completed or still under construction and neighbors of HSR cities (1990-2013)
Pre-treatment periods	• 10 years or more

Notes: 1. The choice of T1 +1 is to ensure that pre-intervention correlation between treated HSR city and its control group cities are not contaminated by the construction of HSR projects (Ching et al. 2012). First, expropriation and demolition could have started before substantive construction. Second, HSR related investment could start sometime before construction started, with the expectation that HSR projects would bring business and investment opportunities. This setting also allows us obtain a sufficient sample size for the pre-intervention period i.e. 10 years at the minimum. 2. For the choice of initial observation t=1, we choose 1990 due to data availability. The reason for the differential setting for costal HSR cities is that at the beginning of the 90's, most of the costal HSR-cities experienced over 20% or 30% per capita real GDP growth rate e.g. Wenzhou, Quanzhou, and Xuzhou etc. However, we do not find extremely high growth for inland HSR-cities or our control group cities within our sample period. To make sure that Eq. (3) holds, we set the initial observation at year 1994 for costal HSR cities. 3. We require pre-intervention period to be at least 10 years, so to obtain a sufficient sample size to estimate the plausibly stable relationship between HSR city and its best predictors. 4. Data source: China City Statistical Yearbook, Provincial Statistical Year Book, China Statistical Yearbook and official documents or news. See text for more details.

14 non-HSR cities by the AICC criterion based on Eq.(8).

Table 3 shows that all the HSR cities along the four HSR lines studied have good in-sample fit with R-square above 0.99 and F-statistic above 120. These results suggest that predictive models chosen by AICC criterion perform well and the per capita real GDP of HSR cities and their predicted counterfactuals are reasonably comparable in the post-treatment period.

Table 3: Summary of in-sample fit performance

Pre-intervention regression			
HSR Lines/Segments	Prefectural-level city	In-sample fit	
		R-square	F-statistic
Beijing-Nanjing Segment on Jing-Hu HSR	Langfang	0.9925	572.5840
	Cangzhou	0.9852	333.2652
	Taian	0.9940	829.7864
	Jining	0.9989	1315.4189
	Xuzhou	0.9981	1593.7235
Hu-Ning Segment on Jing-Hu HSR and Hu-Ning Intercity HSR	Changzhou	0.9986	3468.3830
	Suzhou	0.9985	1956.3034
	Wuxi	0.9999	12427.4726
	Zhenjiang	0.9983	2941.5838
Wu-Guang HSR	Yueyang	0.9925	727.4196
	Changsha	0.9911	1335.4449
	Zhuzhou	0.9932	798.1432
	Hengyang	0.9974	856.9316
	Shaoguan	0.9900	546.1196
	Qingyuan	0.9729	119.5223
Yong-Tai-Wen, Wen-Fu, Fu-Xia Segments on Southeast coast HSR	Taizhou	0.9801	270.7335
	Wenzhou	0.9958	470.7194
	Fuzhou	0.9980	639.7587
	Ningde	0.9979	1553.3681
	Putian	0.9976	936.2872
	Quanzhou	0.9951	252.0547

Notes: 1. This table reports the baseline results for the 21 HSR cities along the four studied HSR projects based on Eq.(8) i.e. $y^0_{1t}=\bar{\alpha}+a^{*\prime}_{-1}y_{-1t}+u^*_{1t}$ using pre-treatment panel sample. 2. Data source: China City Statistical Yearbooks, Provincial Statistical Year Books, and China Statistical Year Books. See text for more details.

4.2 Average Treatment Effects for the treatment group cities

We evaluated the HSR treatment effects in per capita real GDP city by city in log levels using the procedure described in Section 2. Table 4 tabulates actual and hypothetical values of per capita real GDP in log levels, and the estimated treatment effects averaged over the whole policy evaluation period, construction period, and operation period, respectively, for each HSR city.

We analyzed the estimated ATEs in Table 4 from three perspectives:

First, the ATEs of our treatment group cities differed a lot in both sign and magnitude. Panel A suggests that, during the whole policy evaluation period, around 71% of the studied HSR cities had positive ATEs. The ratio is even higher at 86% during the construction period (Panel B), and 62% during the operation period (Panel C). By calculating the 95% confidence interval of the predicted counterfactuals[10], we found that 10 HSR cities[11] had statistically significant HSR effects[12] that were all positive. On the other hand, Table 4 also shows that there are 6 HSR cities

[10] For the 95% confidence interval of the predicted counterfactuals, we graphically illustrate them in Fig. 2 in Section 5.4.

[11] They are Changzhou, Zhenjiang, Wuxi, Xuzhou, Changsha, Zhuzhou, Qingyuan, Fuzhou, Putian, and Quanzhou.

[12] If the annual treatment effects are statistically significant in at least four consecutive policy evaluation periods, we consider them significant.

Table 4: Summary of the average treatment effect

HSR Lines/Segments	City	Panel A: Whole evaluation period			Panel B: Construction period			Panel C: Operation period		
		Actual	Predicted	ATE	Actual	Predicted	ATE	Actual	Predicted	ATE
Beijing-Nanjing Segment on Jing-Hu HSR	Langfang	9.5144	9.541	-0.0265	9.433	9.4009	0.032	9.6922	9.8256	-0.1334
	Cangzhou	9.4184	9.4149	0.0035	9.3363	9.2659	0.0703	9.6028	9.7124	-0.1096
	Taian	9.5345	9.5531	-0.0186	9.4402	9.4489	-0.0087	9.7327	9.7932	-0.0606
	Jining	9.3885	9.405	-0.0165	9.3118	9.2908	0.0211	9.5442	9.6397	-0.0955
	Xuzhou	9.3571	9.2005	0.1566	9.2464	9.1028	0.1436	9.5943	9.4021	0.1922
	Whole route			0.0340			0.0616			-0.0180
Hu-Ning Segment on Jing-Hu HSR and Hu-Ning Intercity HSR	Changzhou	10.3734	10.3041	0.0692	10.2749	10.2016	0.0733	10.5844	10.5153	0.0692
	Suzhou	10.9187	10.8603	0.0584	10.8282	10.7774	0.0508	11.11	11.0477	0.0623
	Wuxi	10.778	10.6742	0.1038	10.6909	10.5632	0.1277	10.9677	10.9072	0.0605
	Zhenjiang	10.2446	101967	0.0479	10.1389	10.0802	0.0586	10.4608	10.4351	0.0256
	Whole route			0.0700			0.0800			0.0600
Wu-Guang HSR	Yueyang	8.967	8.8658	0.1012	8.6982	8.6605	0.0376	9.2986	9.1191	0.1795
	Changsha	9.7575	9.6631	0.0944	9.4412	9.3519	0.0893	10.1729	10.0424	0.1305
	Zhuzhou	9.1161	9.0104	0.1057	8.847	8.7864	0.0605	9.4492	9.2831	0.1662
	Hengyang	8.5804	8.6719	-0.0915	8.3117	8.3707	-0.059	8.9158	9.0502	-0.1344
	Shaoguan	8.9695	9.0589	-0.0893	8.7641	8.8203	-0.0562	9.2219	9.3639	-0.1421
	Qingyuan	8.8448	8.257	0.5878	8.5994	8.1792	0.4202	9.1669	8.3657	0.8011
	Whole route			0.0969			0.0689			0.1368
Yong-Tai-Wen,Wen-Fu,Fu-Xia Segments on Southeast coast HSR	Taizhou	9.5241	9.4982	0.0258	9.3575	9.1813	0.1762	9.7331	9.8982	-0.1652
	Wenzhou	9.451	9.4903	-0.0394	9.2923	9.2733	0.019	9.6485	9.7608	-0.1123
	Fuzhou	9.6636	9.5137	0.1499	9.4439	9.232	0.2119	9.9393	9.8647	0.0747
	Ningde	9.075	9.0481	0.0269	8.7703	8.7465	0.0238	9.4439	9.4138	0.03
	Putian	9.112	8.8371	0.2749	8.9147	8.6424	0.2723	9.5118	9.1979	0.314
	Quanzhou	9.8031	9.5158	0.2873	9.6321	9.3857	0.2464	10.1541	9.7701	0.3839
	Whole route			0.1119			0.1546			0.0709

Notes: 1. This table reports the baseline treatment effects in per capita real GDP averaged over the whole policy evaluation period, the construction and operation period for the 21 HSR cities along the four studied HSR projects, respectively. Per capita real GDP is measured annually. The average treatment effect is defined as the difference between the average actual log per capita real GDP and the average predicted value without the HSR intervention. The overall average treatment effect for the whole route is calculated as the population-weighted average effects of each HSR cities along that route. 2. Data source: China City Statistical Yearbooks, Provincial Statistical Year Books, and China Statistical Year Books. See text for more details.

with negative ATEs, but none of them is statistically significant at 5% level. In summary, the projects had significantly raised the per capita GDP for 48% of our treatment group cities, while for the rest we found no significant HSR impact. Among those with significant HSR impacts, the magnitude of the ATEs ranged between a minimum of 5% for Zhenjiang on Hu-Ning Segment and a maximum of 59% for Qingyuan on Wu-Guang HSR. Most of the ATEs were larger than 10%, indicating that for cities that significantly gained from HSR projects, local income increased at least 10% more than if there had been no HSR projects within our policy evaluation period.

Second, we examined the spatial distribution of the ATEs and found that on a route level the HSR cities with positive ATEs concentrated along the Hu-Ning Segment and Yong-Tai-Wen-Fu-Xia Segment. At a regional level, they were mainly located along China's east coast. The two segments connect cities in the Yangtze River Delta[13] and in the west coast of the Straits. Cities with positive and significant effects geographically concentrate in the core urban cluster in the above two regions, i.e., Zhenjiang, Changzhou, and Wuxi in the Yangtze River Delta and Fuzhou, Putian, and Quanzhou on the west coast of the Straits. Among the four HSR cities in the Hunan province on Wu-Guang HSR line, Yueyang, Changsha, and Zhuzhou have positive ATEs. The latter two had positive and statistically significant treatment effects and are the two main members of the core urban cluster of the Chang-Zhu-Tan area in Hunan province.[14] In contrast, along the Beijing-Nanjing Segment on Jing-Hu HSR and the rest of Wu-Guang HSR, only Xuzhou and Qingyuan had significant and positive ATEs, but the magnitude of income growth was substantial. The impact on both cities does not come as a surprise. Xuzhou is a historical thoroughfare connecting five adjacent provinces. Their special location not only makes Xuzhou an important comprehensive transportation hub on the national level but also one of the central urban clusters in the Yangtze River Delta. Qingyuan, located along one of the main streams of Pearl River, is adjacent to Guangzhou and has many beautiful natural landscapes. Its the function of the hub and its resources for tourism can explain the substantial increase in per capita GDP due to HSR.

Third, we checked the temporal distribution of the ATEs and found that the ATEs for the two different project stages differ. Our results show that 57% of the 21 HSR cities had larger ATEs in the construction period than in the early operation period. The finding seems to be consistent with the finding for U.S. interstate highway that there was a declining effect of transportation infrastructure as it evolved through different stages (e.g. Fernald, 1999).

4.3 Average Treatment Effects of the Whole Route

Because the average treatment effects differ by route and cities, we suggest measuring the average treatment of the i th route by

$$ATE(i) = \sum_{j=1}^{q_{ij}} w_{ij} ATE_i(j) \,, \quad j = 1,2,...,q_{ij}, i = 1,2,3,4 \qquad (15)$$

[13] The Yangtze River Delta generally comprises the triangle-shaped territory of Wu-speaking Shanghai, the southern Jiangsu province, and the northern Zhejiang province of China. The area lies at the heart of the Yangtze River, which drains into the East China Sea, has fertile soil and produces grain, cotton, hemp, and tea. For details, please refer to the Regional Planning of Yangtze River Delta approved by the State Council in 2010.

[14] In this urban cluster, Changsha, Zhuzhou and Xiangtan are located quite near each other with pair-wise distance less than 20 kilometers.

where $ATE_i(j)$ indicates the ATE of the j th city at the i th route, q_{ij} denotes the number of cities analyzed for the i th route, and w_{ij} is the relative weight of the j th city at the i th route so $\sum_{j=1}^{q_{ij}} w_{ij} = 1$. We compute

$$w_{ij} = \frac{p_{ij}}{\sum_{j=1}^{q_{ij}} p_{ij}}, \tag{16}$$

where p_{ij} denotes the average population during the period of the j th city at route i. The i-th route ATE is also presented at Table 4.

Table 4 suggests that the overall average treatment effects of the whole route for the four studied HSR projects were positive, with a magnitude ranging from 3.4% to 15.5%, during various policy evaluation periods. This result confirms that these HSR construction projects in China cause local economic growth for the whole route, although some locations gain more while others benefit less. The only exception is the Beijing-Nanjing Segment on Jing-Hu HSR in early operation period 2011-2013, the overall average impact is -1.8% with a small magnitude. This negative result is similar with Li (2000)'s finding that during the first two years of operation, the provincial output along Jing-Hu HSR corridor decreased compared to the values if there had been no HSR project, because of the crowding out effect of both public and private investment to other sectors. Our result is also consistent with the fact that the Beijing-Nanjing Segment is a cross-regional transportation corridor passing through Hebei, Shandong, Anhui, and Jiangsu provinces. The natural endowments, industrial structure, social economic conditions, and local government policies could differ substantially between North and East China and among provinces, thus leading to the disparate local gains or losses from HSR projects and bringing much more variation to the benefit of the whole segment.

4.4 Detailed illustration

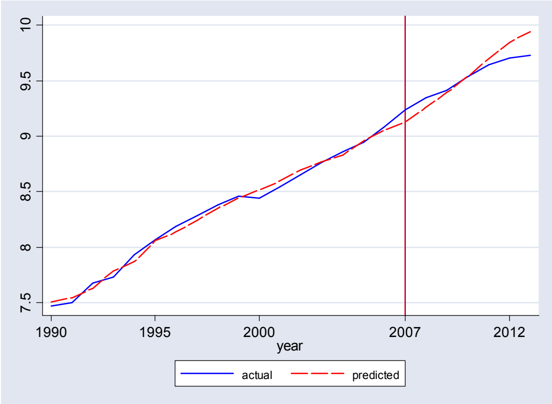
We used one or two cities for each HSR line/segment. Fig. 2 illustrates the detailed treatment effect results for five HSR cities, designed to graphically show the dynamics, trends, and the statistical significance of the annual treatment effects. Table 5 tabulates the estimated values accordingly.

For the pretreatment period, Panel A of Table 5 lists the control cities selected by AICC criterion to construct the hypothetical per capita real GDP path for the five HSR cities respectively. The upper row of Fig. 2 shows that the counterfactual path of per capita real GDP produced by the selected control group cities closely adheres to the actual path for all the five HSR cities.

For the post-treatment period, Fig. 2 shows that the annual effects of treatment in per capita real GDP are uniformly positive for Xuzhou on the Beijing-Nanjing Segment (Panel B), Changzhou on the Hu-Ning Segment (Panel C), Qingyuan on the Wu-Guang HSR (Panel D), and Quanzhou on the Yong-Tai-Wen-Fu-Xia Segments (Panel E), although the magnitudes differ. In

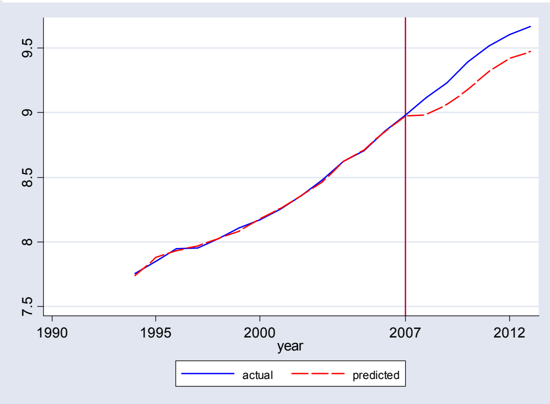
Panel A Langfang on Beijing-Nanjing Segment

A1: the whole sample period, 1990-2013

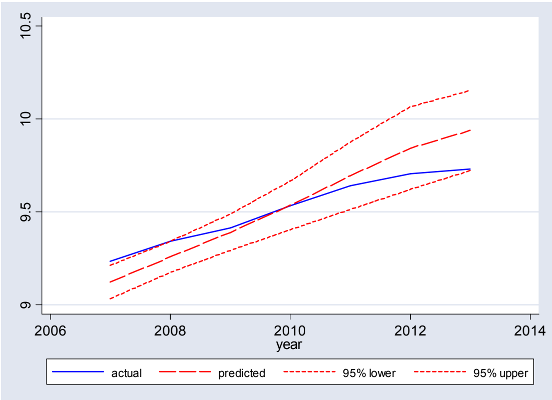


Panel B Xuzhou on Beijing-Nanjing Segment

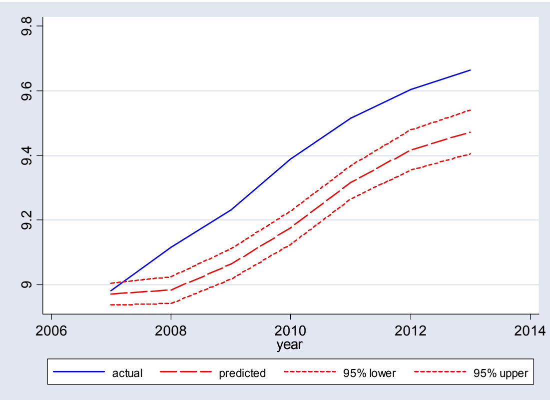
B1: the whole sample period, 1994-2013



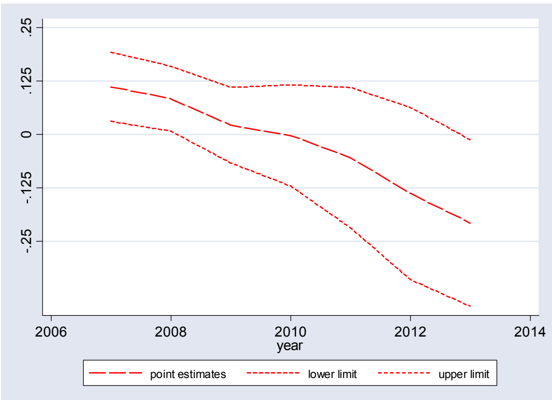
A2: the post-treatment period, 2007-2013



B2: the post-treatment period, 2007-2013



A3: the treatment effects, 2007-2013



B3: the treatment effects, 2007-2013

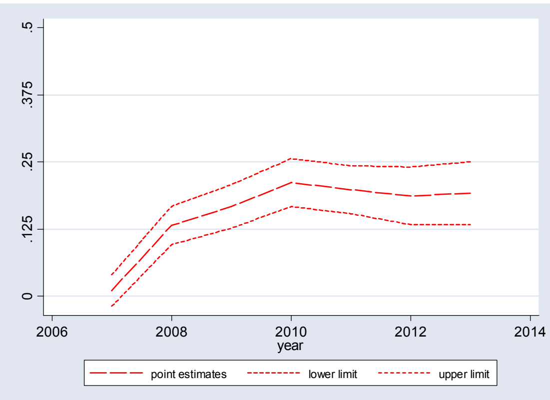
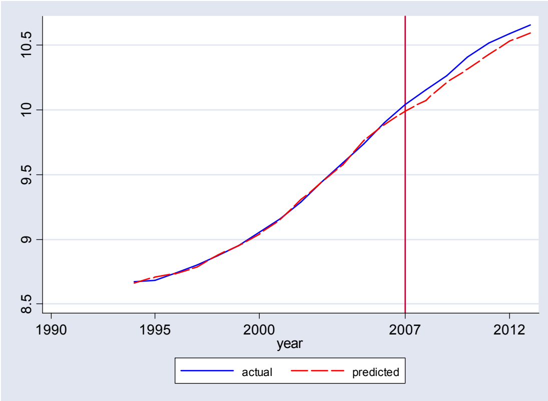


Fig. 2. Baseline results: Treatment effects in per capita real GDP for the five HSR cities. Notes: 1. Figures A1-E1 plot the actual and hypothetical series of per capita real GDP in log levels for the whole sample period. The vertical line denotes the cut-off point T_1+1. Figures A2-E2 plot both series during the post-treatment period and the dotted lines denote the 95 percent confidence bands of the predicted counterfactuals. Figures A3-E3 directly plot the point estimates of treatment effects and their interval estimates following Hsiao (2014). 2. "actual" indicates the actual path; "predicted" indicates the predicted outcome based on pre-treatment observations. See Table 5 for the estimation results for the five HSR cities. 3. Data source: China City Statistical Yearbooks, Provincial Statistical Year Books, and China Statistical Year Books. See text for more details.

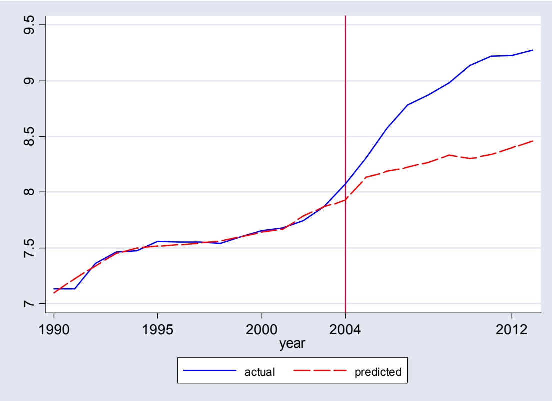
Panel C Changzhou on Hu-Ning Segment

C1: the whole sample period, 1994-2013

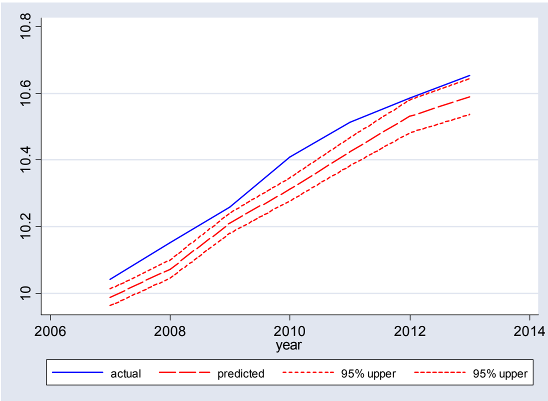


Panel D Qingyuan on Wu-Guang HSR

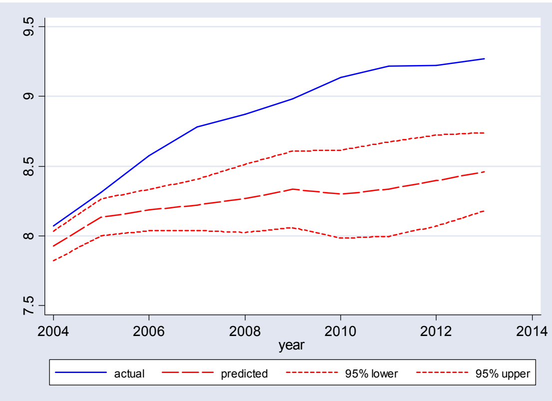
D1: the whole sample period, 1990-2013



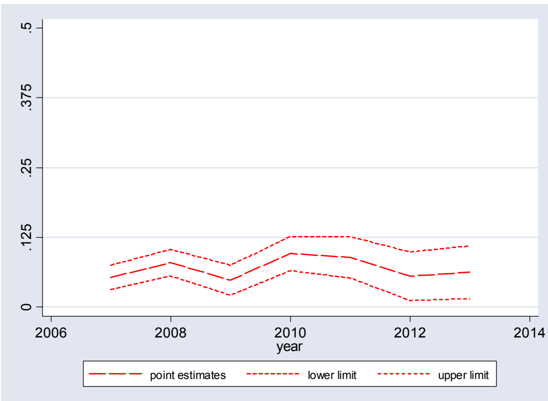
C2: the post-treatment period, 2007-2013



D2: the post-treatment period, 2004-2013



C3: the treatment effects, 2007-2013



D3: the treatment effects, 2004-2013

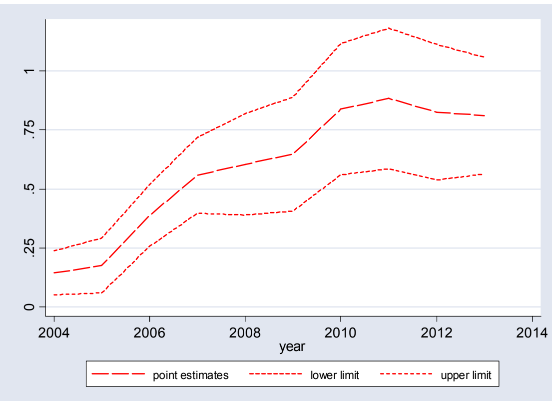
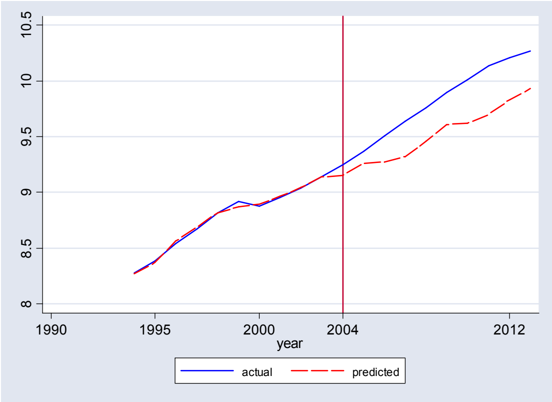


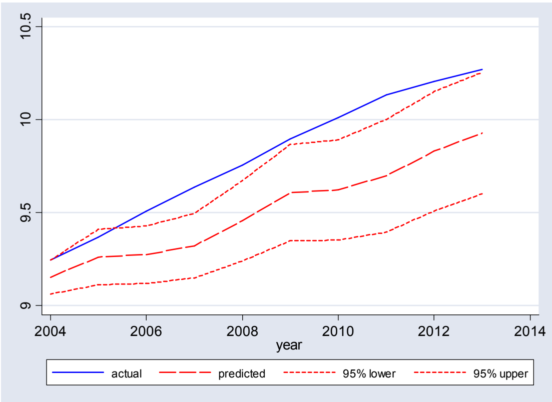
Fig. 2. (*continued*)

Panel E Quanzhou on Yong-Tai-Wen-Fu-Xia Segments

E1: the whole sample period, 1994-2013



E2: the post-treatment period, 2004-2013



E3: the treatment effects, 2004-2013

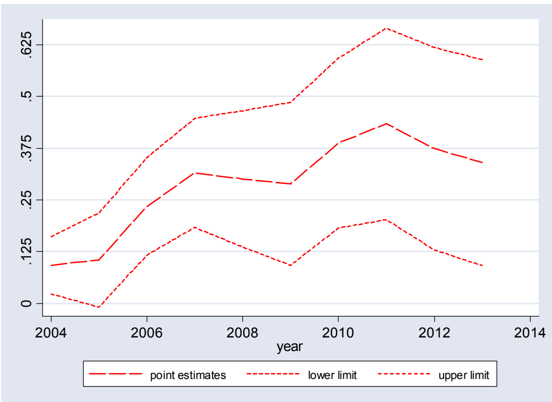


Fig. 2. (*continued*)

contrast, for Langfang on the Beijing-Nanjing Segment, the impact was not uniformly positive (Panel A).

The dynamics of the annual impact were similar for the four HSR cities with positive impacts. Specifically, as early as one year before construction started, the growth path of per capita real GDP significantly changed compared to the case had there been no HSR projects. In subsequent years, the treatment effects were relatively stable for Changzhou and Xuzhou throughout the construction and operation periods. For Quanzhou and Qingyuan, there is an increasing trend of treatment effects during the construction period. During the operation period the impacts are relatively stable. The results strongly suggest that these HSR projects continuously raised the per capita real GDP for the four locations, instead of producing a temporary effect. Actually, it is the case for most treatment group cities with significant impacts. The middle row of Fig. 2 indicates that the continuous positive impacts were also significant at 5% level. Although 7-10 years after the construction of HSR projects is a bit short to estimate the long-term treatment effects, it seems a reasonable projection. Conditional on the stable HSR impacts throughout the operation period, we expected that this significant and relatively stable impact would continue. In addition, the magnitude of the ATEs, listed in ascending order is Changzhou (6.92%), Xuzhou (15.66%) Quanzhou (28.73%) and Qingyuan (58.78%) (Panel B of Table 5).

Unlike the above four cities, it is only in the early construction period that Langfang's treatment effects were positive and significant (Panel A). The impacts then decrease, finally becoming negative and are not significant at the 5% level. Panel B of Table 5 shows that the ATEs for Langfang are -2.65%，3.2%，and -13.34% for the whole evaluation period, construction period, and operation period, respectively.

5. Factors Affecting Disparity of HSR impacts

We find that the impacts of HSR differ among cities and routes. In this section, we investigate factors affecting the disparity of HSR impacts. We note that locations differ in endowments, accessibility, and in many other first- and second-nature characteristics (e.g. Behrens & Robert-Nicoud, 2015). European evidence also suggests that the impact of HSR is different between small and big cities and the first tier cities tend to gain (Urena et al., 2009). The impact could also depend on the specific situation of initial levels of accessibility and the change in them (Vickerman & Ulied, 2006). Moreover, the main function of a hub is catalytic (Fujita et al., 1999). For example, Langfang is located between the capital Beijing and the municipality Tianjin. It is just 40 km to Tian'anmen Square and 60 km to the center of Tianjin. Moreover, its administrative subordinating relationship has changed many times. The theory of hierarchy structure of city systems suggests that within a threshold of distance from mega cities, there can hardly be any other big cities.

To answer this question, we conduct regression analysis by relating HSR impacts to a series of city characteristics,

$$\hat{\Delta}_{it} = \alpha + X_{it}\beta + u_i + v_t + \varepsilon_{it} , \quad (17)$$

where i and t denote location and year respectively. The dependent variable $\hat{\Delta}_{it}$ is the HSR impacts in per capita real GDP estimated in Section 4. For explanatory variables X_{it} , we consider industrial structure measured by both the sectoral output shares and employment shares of manufacturing and service industries, city characteristics such as city size, the condition of supporting infrastructures, human capital stock, average wage rate, as well as an index for tourism attractions (Guirao et al., 2015; Lin, 2014; Vickerman & Ulied, 2006). Moreover, even after 30 years of economic development and transition, China today still bears some of the characteristics of a planned economy, noticeably investment and international trade-driven growth, high shares of manufacturing in the national economy, and a large sector of state-owned enterprises (SOE) etc. (Yao, 2014). To see whether and how these important structural features of the Chinese economy play a role in explaining the impact of HSR projects, we include the output share of FDI, fixed

Table 5: Results of the five HSR cities for detailed illustration

Langfang on Beijing-Nanjing Segment				Xuzhou on Beijing-Nanjing Segment				Changzhou on Hu-Ning Segment & Hu-Ning Intercity			
Panel A: Estimated Weights of Control Groups, 1990-2006				Panel A: Estimated Weights of Control Groups, 1994-2006				Panel A: Estimated Weights of Control Groups, 1994-2006			
Cities	weights	SD	T	Cities	weights	SD	T	Cities	weights	SD	T
Yancheng	0.7866	0.348	2.26	Yancheng	0.8129	0.0478	17	Yancheng	0.443	0.0422	10.5
Jinchang	-0.152	0.0442	-3.44	Yinchuan	-0.2487	0.0821	-3.03	Hohhot	0.3847	0.027	14.25
Time trend	0.0284	0.0339	0.84	Jinchang	0.2261	0.0347	6.52				
R^2	0.9925			R^2	0.9981			R^2	0.9986		
F-stats	572.584			F-stats	1593.7235			F-stats	3468.383		
Panel B: Treatment Effects, 2007-2013											
Year	Actual	Predicted	Treatment	Year	Actual	Predicted	Treatment	Year	Actual	Predicted	Treatment
2007	9.2353	9.1237	0.1116	2007	8.9817	8.9716	0.0101	2007	10.0408	9.9876	0.0532
2008	9.3426	9.259	0.0836	2008	9.1155	8.984	0.1315	2008	10.1522	10.0725	0.0797
2009	9.4132	9.3915	0.0217	2009	9.2316	9.0646	0.167	2009	10.2592	10.2109	0.0483
2010	9.5334	9.5358	-0.0024	2010	9.3884	9.177	0.2114	2010	10.4081	10.3122	0.096
2011	9.6403	9.6947	-0.0544	2011	9.5149	9.3168	0.1981	2011	10.5141	10.4247	0.0894
2012	9.7055	9.8438	-0.1383	2012	9.6035	9.4168	0.1867	2012	10.5863	10.531	0.0554
2013	9.7307	9.9382	-0.2074	2013	9.6644	9.4727	0.1917	2013	10.6529	10.5903	0.0627
average 2007-2011	9.5144	9.541	-0.0265	average 2007-2011	9.3571	9.2005	0.1566	average 2007-2011	10.3734	10.3041	0.0692
average 2011-2013	9.433	9.4009	0.032	average 2011-2013	9.2464	9.1028	0.1436	average 2011-2013	10.2749	10.2016	0.0733
average	9.6922	9.8256	-0.1334	average	9.5943	9.4021	0.1922	average	10.5844	10.5153	0.0692

Notes: 1. The table reports the baseline estimated results for per capita real GDP in log level. Per capita real GDP is measured annually. Panel A reports the results from pre-treatment regression $y_{1t}^{0}=\bar{\alpha}+a_{-1}^{*\prime}y_{-1t}+u_{1t}^{*}$. Panel B reports the estimated annual treatment effects, which is the difference between actual data and the predicted values approximated using the weights listed in Panel A. It also reports the treatment effects averaged over the whole policy evaluation period, the construction and operation period for the four HSR projects respectively. 2. Data source: China City Statistical Yearbooks, Provincial Statistical Year Books, and China Statistical Year Books. See text for more details.

Table 5: *(continued)*

Qingyuan on Wu-Guang HSR				Quanzhou on Yong-Tai-Wen-Fu-Xia Segment			
Panel A: Estimated Weights of Control Groups, 1990-2003				Panel A: Estimated Weights of Control Groups, 1994-2003			
Cities	weights	SD	T	Cities	weights	SD	T
Baotou	0.4128	0.094	4.39	Zhoushan	-1.7119	0.3227	-5.3
Shuangyashan	-0.6363	0.2093	-3.04	Tonghua	0.0834	0.2253	0.37
Yancheng	0.5262	0.1873	2.81	Baotou	0.5622	0.1474	3.81
				Time trend	0.2031	0.017	11.97
R^2	0.9729			R^2	0.9951		
F-stats	119.5223			F-stats	252.0547		
Panel B: Treatment effects, 2004-2013							
Year	Actual	Predicted	Treatment	Year	Actual	Predicted	Treatment
2004	8.0733	7.9285	0.1449	2004	9.246	9.1535	0.0925
2005	8.3106	8.1343	0.1763	2005	9.3664	9.2617	0.1047
2006	8.5747	8.1862	0.3885	2006	9.5093	9.2749	0.2344
2007	8.7814	8.2229	0.5585	2007	9.6382	9.3226	0.3156
2008	8.8737	8.2692	0.6045	2008	9.7577	9.4566	0.3011
2009	8.9826	8.3343	0.6482	2009	9.8974	9.6082	0.2892
2010	9.1382	8.3	0.8382	2010	10.0098	9.6222	0.3876
2011	9.2196	8.3363	0.8833	2011	10.1329	9.699	0.4339
2012	9.223	8.3975	0.8255	2012	10.2045	9.8306	0.3739
2013	9.271	8.4606	0.8104	2013	10.269	9.9287	0.3403
average	8.8448	8.257	0.5878	average	9.8031	9.5158	0.2873
2004-2009				2004-2010			
average	8.5994	8.1792	0.4202	average	9.6321	9.3857	0.2464
2009-2013				2010-2013			
average	9.1669	8.3657	0.8011	average	10.1541	9.7701	0.3839

asset investments, and the employment share of SOEs[15] as proxies for monopoly power by local states.

Regression results for the whole treatment period are reported in Table 6. Column 1 to 6 in Panel A shows that for the whole policy evaluation period, regardless of whether the base set or additional controls for city characteristics are included, sectoral output shares of manufacturing and employment shares of service are positively and significantly correlated with the estimated treatment effects at the 1% level. Specifically, having a one percent increase in the output share of manufacturing is associated with at least a 1.2 percent increase in HSR treatment effect in per capita GDP. The positive correlation between sectoral employment share of service and treatment effects is even higher, at least 1.6 percent. We also find that cities with good supporting infrastructure or accessibility benefit from the HSR. Almost all the HSR stations in China are built in the suburbs, better supporting infrastructure is a necessary condition for HSR service to be fully utilized to stimulate local economic development. In addition, the indicator for tourism resources is positively and significantly correlated with the treatment effects, suggesting that popular tourists' destinations could benefit significantly from HSR projects (Lin, 2014; Guirao et al., 2015). These findings are consistent with the European experience (see Vickerman & Ulied, 2006).

We also conducted treatment effects regression separately for the construction and operation periods. Panel B shows that, during the construction period, the sectoral output share of manufacturing is positively and significantly correlated with the HSR impacts with a similar magnitude as for the whole policy evaluation period. The result is very robust for various controls. Columns 8 to 10 suggest that large targeted cities are more likely to gain from HSR projects during the construction period, and the result is significant and robust. This finding corroborates those in European studies, but it also differs in the sense that we only find positive city size effects during the construction period. We notice that in the early operation period, the coefficient of city size is negative but not statistically significant (Panel C). One potential reason for the insignificance could be due to the short operation period.

Panel C indicates that, for the early operation period, the sectoral employment shares of both manufacturing and service play an important role in explaining the disparity in the effects of treatment, with the service sector having a larger impact. One notable result is that local protectionism is negatively and significantly correlated with the impact of HSR projects. If one considers that cities with strong local protection could suffer from increased competition due to an improved transportation network and that SOE employment could be a proxy for local protection, this finding suggests that when HSR projects open to public, local residents could lose the benefit of local protection. This by-product of our study seems to be consistent with the view expressed in Banerjee et al. (2012) that a lack of factor mobility could limit the impact of transportation infrastructure, in that factor mobility tends to be restricted in locations with severe local protectionism for both labor and capital. Column 14 further supports this view since it shows that cities having larger proportion of the population with tertiary education tend to gain. As university educated passengers constitute around 60% of the passenger flow for HSR in China, the positive relationship is intuitive. Similar to the whole policy evaluation period,

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[15] The SOE employment ratio is measured at the provincial level because the data for SOE employees is not available at prefectural city-level. We tried to use the number of private-enterprise and self-employed individuals in an urban employment at prefectural city-level instead, but it is not significant.

Table 6: Effect of city characteristics on estimated treatment effects (the whole policy evaluation period, construction, operation period)

	Panel A: Whole policy evaluation period						Panel B: Construction period				Panel C: Operation period			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Industrial share in GDP	1.272***		1.299***	1.196***	1.923***	2.144***	1.357***	1.414***	1.246***	1.223***				
	(0.255)		(0.219)	(0.114)	(0.473)	(0.468)	(0.134)	(0.124)	(0.151)	(0.163)				
Services share in GDP	0.903*		0.916	1.131*	1.580**	1.665**	0.199	0.391	0.214	0.156				
	(0.509)		(0.559)	(0.597)	(0.687)	(0.636)	(0.408)	(0.371)	(0.361)	(0.386)				
Industrial share in employment		1.742***	1.110*	0.987*	0.758	0.962					1.949***	1.702***	1.723***	1.288**
		(0.531)	(0.533)	(0.520)	(0.585)	(0.604)					(0.465)	(0.564)	(0.499)	(0.482)
Services share in employment		2.353***	1.847***	1.605***	1.600***	1.838***					2.021***	1.750***	1.852***	1.488***
		(0.540)	(0.476)	(0.487)	(0.524)	(0.556)					(0.424)	(0.493)	(0.456)	(0.438)
City size				-0.0242	-0.0194	-0.0279**		0.0383*	0.0364*	0.0306*		-0.0154	-0.011	-0.0226
				(0.016)	(0.014)	(0.012)		(0.019)	(0.019)	(0.018)		(0.012)	(0.014)	(0.015)
Road density				0.158**	0.131*	0.102		0.0761	0.0994	0.0928*		0.000555	-0.0598	-0.0288
				(0.059)	(0.065)	(0.068)		(0.061)	(0.061)	(0.053)		(0.095)	(0.118)	(0.107)
Ln(average wage)				0.385	0.455	0.404*		-0.00212	-0.0403	-0.0327		0.134	0.272	0.262
				(0.253)	(0.265)	(0.227)		(0.215)	(0.224)	(0.242)		(0.259)	(0.194)	(0.186)
Fixed asset investment ratio					-0.412	-0.477			0.0544	0.00228			-0.0341	-0.0284
					(0.263)	(0.285)			(0.098)	(0.093)			(0.057)	(0.052)
FDI					-0.0122	-0.0553			1.129	1.62			-0.946	-0.0219
					(0.914)	(1.245)			(0.768)	(1.038)			(2.207)	(2.200)
Size of SOE employment					-0.103	-0.113			0.615	0.723			-0.613***	-0.560**
					(0.392)	(0.344)			(0.484)	(0.485)			(0.190)	(0.198)
Univ. enroll per 10 thousand people						0.296				0.101				0.613***
						(0.288)				(0.307)				(0.166)
Star hotel						0.223*				-0.105				0.147**
						(0.110)				(0.101)				(0.062)
Number of observations	183	183	183	183	183	181	104	104	104	102	79	79	79	79
Number of cities	21	21	21	21	21	21	21	21	21	21	21	21	21	21
R^2(within)	0.124	0.055	0.188	0.288	0.369	0.41	0.415	0.443	0.458	0.464	0.375	0.372	0.486	0.522

Notes: 1. * p<0.10, ** p<0.05, *** p<0.01. 2. All specifications report cluster-robust standard errors in parentheses, clustered at the city level. 3. All regressions control for city fixed effects and year fixed effects. 4. Panel A give the results for the whole policy evaluation period. Panel B and Panel C are the results for the construction and operation period respectively. 5. For more degrees of freedom in our panel regression, I drop the sectoral employment shares (industry and services) in the construction period. While I drop the sectoral output shares (industry and services) for the operation period, because none of them is statistically significant in respective project stages. 6. The SOE employment ratio is measured at provincial-level, because for prefectural-level city, the number of SOE employees is not available. The number of private-enterprise and self-employed individual in urban employment at prefectural-city level is available, we tried to include it but it is not significant. 7. Data sources: All variables are obtained from the China City Statistical Yearbook for 2005-2014, except for the number of SOE employee and total number of employee, which are from the China Statistical Yearbook for the same years.

tourism resources are positively and significantly correlated with the treatment effects.

6. Robustness check

To evaluate the credibility of our baseline treatment effects estimates in Sections 4.1 and 4.2, we conducted two robustness checks.

6.1 Sensitivity test

We tested the sensitivity of the above baseline results to changes in the control group. Recall from Section 3.2 that most of the 14 baseline control group cities are from remote regions in China. Here we re-estimate Eq. (8) by using a new control group constituted of non-HSR cities from regions that are geographically and economically close to our HSR cities, such as neighbors of HSR cities, cities from contiguous provinces, and cities with similar magnitude of per capita real GDP levels to our HSR cities during sample period 1990-2013. If the baseline results are sensitive to this change, estimation results based on the new control group will significantly differ from the above baseline results. Table 7 lists the new control group cities.

Table 7: The new control group cities

Prefectural-level control group cities	Province	Region
Lianyungang, Nantong, Yangzhou, Huaian, Taizhou, Suqian	Jiangsu	East
Huzhou	Zhejiang	East
Sanming	Fujian	East
Dongying, Laiwu, Rizhao, Weihai	Shandong	East
Huaibei, Anqing	Anhui	East
Zhangjiakou, Chengde	Hebei	North
Changde	Hunan	Middle

Notes: 1. We chose the 17 new control group cities because their total GDP and population data were available and consistent for the whole sample period 1990-2013. We did not exhaust all non-HSR neighbors concerning our treatment group. 2. Data source: National Railway Administration of the People's Republic of China.

As for the baseline results, Tables 8 and 9 report the treatment effect estimation results for the 21 HSR cities based on the new control group, including in sample fit performance and ATEs. We further use Fig.3 to graphically show the robustness of baseline treatment effects for the five HSR cities as illustration.

Table 8 shows that, for all the HSR cities, R-square is equal to or above 0.99 and F-statistic is above 200, which indicate that the predictive model base on the new control group performs as well as for the benchmark results.

By comparing Table 9 and Table 4, we can see that the results of the baseline estimates are robust in both sign and magnitude for most of the treatment group cities when we change the control group. Panel A demonstrates that, during the whole policy evaluation period, the signs of the estimated ATEs for the 21 HSR-cities based on the baseline control group are the same as those based on the new control. In addition, the magnitudes of the ATEs for all the 21 HSR-cities in the baseline model are similar to those in the sensitivity checks, except for Cangzhou and Wenzhou.

Table 8: Summary of in-sample fit performance

Pre-intervention regression			
HSR Lines/Segments	Prefectural-level city	In-sample fit	
		R-square	F-statistic
Beijing-Nanjing Segment on Jing-Hu HSR	Langfang	0.9993	2111.73
	Cangzhou	0.9991	1633.4851
	Taian	0.9951	2219.0381
	Jining	0.9974	2476.2951
	Xuzhou	0.9982	2373.7083
Hu-Ning Segment on Jing-Hu HSR and Hu-Ning Intercity HSR	Changzhou	0.9991	5035.6937
	Suzhou	0.9943	1226.7269
	Wuxi	0.9980	1082.4727
	Zhenjiang	0.9986	3003.8348
Wu-Guang HSR	Yueyang	0.9959	541.289
	Changsha	0.9935	345.7289
	Zhuzhou	0.9965	644.9763
	Hengyang	0.9844	346.6435
	Shaoguan	0.9950	446.2776
	Qingyuan	0.9926	303.5182
Yong-Tai-Wen, Wen-Fu, Fu-Xia Segments on Southeast coast HSR	Taizhou	0.9906	236.4921
	Wenzhou	0.9975	1353.2956
	Fuzhou	0.9989	1446.6916
	Ningde	0.9983	1356.8269
	Putian	0.9894	309.9731
	Quanzhou	0.9934	498.6869

Notes: 1. The table reports the sensitivity test results based on the new control group constituted of non-HSR cities from geographically and economically close-by regions to our treatment group cities. 2. Data source: China City Statistical Yearbooks, Provincial Statistical Year Books, and China Statistical Year Books. See text for more details.

Panel B suggests that, during the construction period, the signs of the ATEs for all HSR cities in the baseline results are the same as those based on the new control group except for Langfang, Jining, and Ningde. During the early operation period, only Cangzhou and Taizhou differ in sign between the baseline and sensitivity checks.

To further test the robustness for the treatment effects in the five cities, we constructed a 95% confidence band of the effects under the benchmark setting. If the impacts estimated using the new control group falls into this confidence band, then our interpretation is that the effects did not differ significantly from the baseline results. Results show that, for Langfang, Jining, Cangzhou, and Taizhou[16], the impacts were robust. For Ningde, the treatment effects in 2008-2010 fell into the confidence band.

Using the five HSR cities as illustration, Fig. 3 shows that for the pretreatment period, the counterfactual per capita real GDP constructed based on the new control group almost overlap the actual path for all the five HSR cities. As expected, adding neighbors of HSR cities to the control group further improves the in-sample fit performance.

For the policy evaluation period, the annual treatment effects remained qualitatively unchanged not only in sign but also in dynamics. For the magnitude, the values of ATEs are similar to the baseline results and sensitivity tests for Langfang, Changzhou, and Qingyuan. On the other hand, the values for Xuzhou (7.6%) and Quanzhou (16.6%) are quantitatively noticeably lower than the baseline estimates of 15.6% and 28.7%. However, neither pairs of values differ significantly. The bottom rows of Fig. 2 and Fig. 3 suggest that the interval

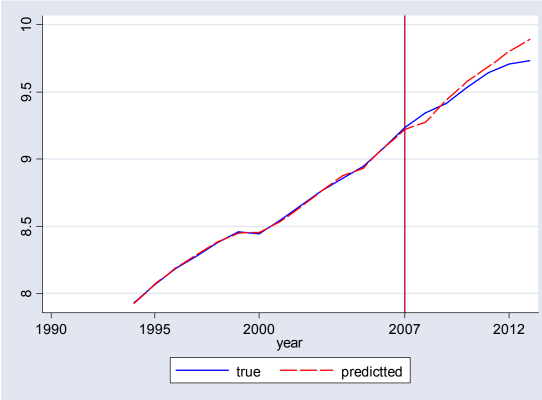
[16] The 95% confidence band for Taizhou seems to be rather large due to the large prediction error.

Table 9: Summary of the average treatment effect

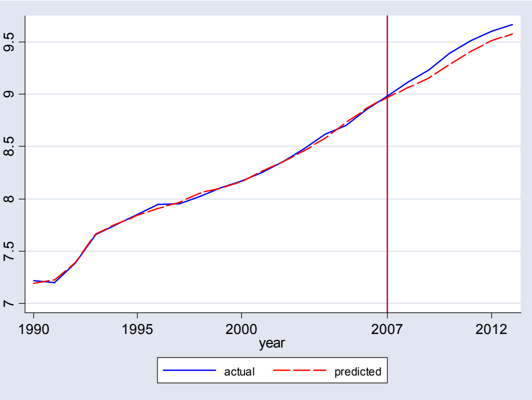
HSR Lines/Segments	City	Panel A: Whole evaluation period			Panel B: Construction period			Panel C: Operation period		
		Actual	Predicted	ATE	Actual	Predicted	ATE	Actual	Predicted	ATE
Beijing-Nanjing Segment on Jing-Hu HSR	Langfang	9.5144	9.5551	-0.0406	9.433	9.4396	-0.0067	9.6922	9.7909	-0.0987
	Cangzhou	9.4184	9.3878	0.0306	9.3363	9.3051	0.0312	9.6028	9.5456	0.0572
	Taian	9.5345	9.5642	-0.0297	9.4402	9.4544	-0.0142	9.7327	9.7952	-0.0625
	Jining	9.3885	9.4144	-0.0258	9.3118	9.3263	-0.0145	9.5442	9.5953	-0.0512
	Xuzhou	9.3571	9.2808	0.0763	9.2464	9.1763	0.0701	9.5943	9.4978	0.0964
Hu-Ning Segment on Jing-Hu HSR and Hu-Ning Intercity HSR	Changzhou	10.3734	10.3255	0.0479	10.2749	10.2254	0.0495	10.5844	10.5352	0.0493
	Suzhou	10.9187	10.8847	0.0340	10.8282	10.8003	0.0278	11.11	11.0517	0.0583
	Wuxi	10.778	10.6693	0.1087	10.6909	10.5910	0.0999	10.9677	10.8156	0.1522
	Zhenjiang	10.2446	10.1935	0.0511	10.1389	10.0950	0.0439	10.4608	10.3973	0.0635
Wu-Guang HSR	Yueyang	8.967	8.9002	0.0668	8.6982	8.6674	0.0308	9.2986	9.1851	0.1135
	Changsha	9.7575	9.6940	0.0635	9.4412	9.3886	0.0526	10.1729	10.0705	0.1024
	Zhuzhou	9.1161	8.9868	0.1293	8.847	8.7631	0.0839	9.4492	9.2600	0.1893
	Hengyang	8.5804	8.6821	-0.1017	8.3117	8.4045	-0.0928	8.9158	9.0294	-0.1136
	Shaoguan	8.9695	9.0560	-0.0865	8.7641	8.8682	-0.1042	9.2219	9.2957	-0.0739
	Qingyuan	8.8448	8.3090	0.5358	8.5994	8.1929	0.4065	9.1669	8.4581	0.7088
Yong-Tai-Wen,Wen-Fu,Fu-Xia Segments on Southeast coast HSR	Taizhou	9.5241	9.4568	0.0673	9.3575	9.2985	0.0590	9.7331	9.6437	0.0893
	Wenzhou	9.451	9.4551	-0.0042	9.2923	9.2670	0.0253	9.6485	9.6877	-0.0392
	Fuzhou	9.6636	9.4996	0.1640	9.4439	9.3196	0.1244	9.9393	9.7201	0.2193
	Ningde	9.075	9.0351	0.0400	8.7703	8.8209	-0.0506	9.4439	9.2914	0.1525
	Putian	9.112	8.8836	0.2284	8.9147	8.7422	0.1725	9.5118	9.1771	0.3347
	Quanzhou	9.8031	9.6371	0.1661	9.6321	9.4869	0.1452	10.1541	9.9329	0.2212

Notes: 1. The table reports the sensitivity test results of estimated average impacts based on a new control group constituted of non-HSR cities from geographically and economically close-by regions to our HSR cities. 2. Data source: China City Statistical Yearbooks, Provincial Statistical Year Books, and China Statistical Year Books. See text for more details.

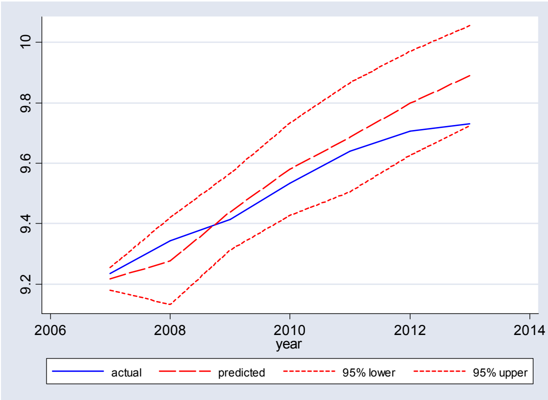
Panel A Langfang on Beijing-Nanjing Segment
A1: the whole sample period, 1994-2013



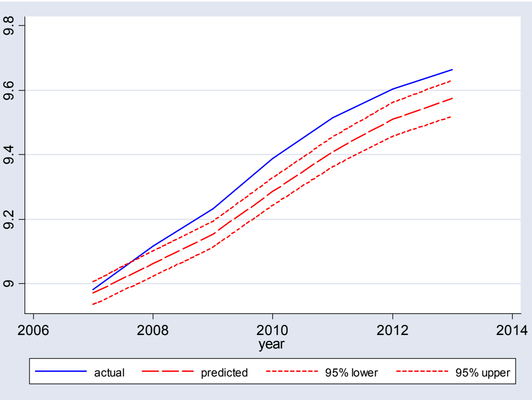
Panel B Xuzhou on Beijing-Nanjing Segment
B1: the whole sample period, 1990-2013



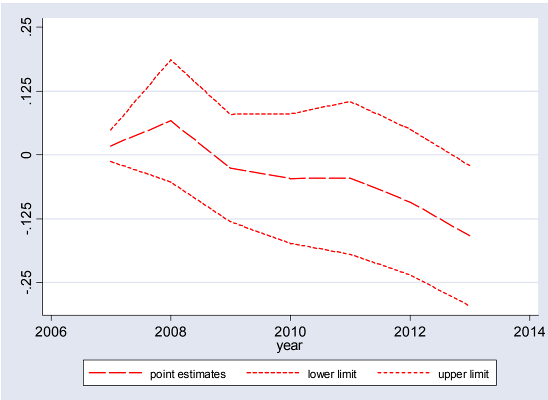
A2: the post-treatment period, 2007-2013



B2: the post-treatment period, 2007-2013



A3: the treatment effects, 2007-2013



B3: the treatment effects, 2007-2013

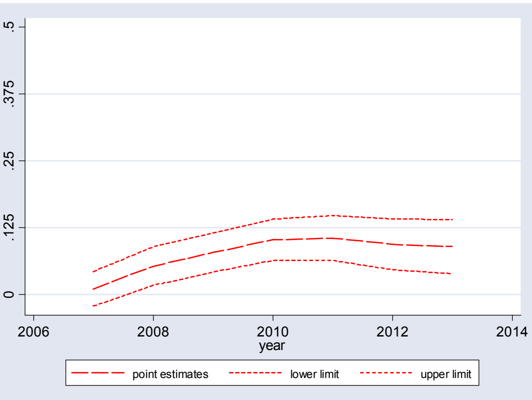
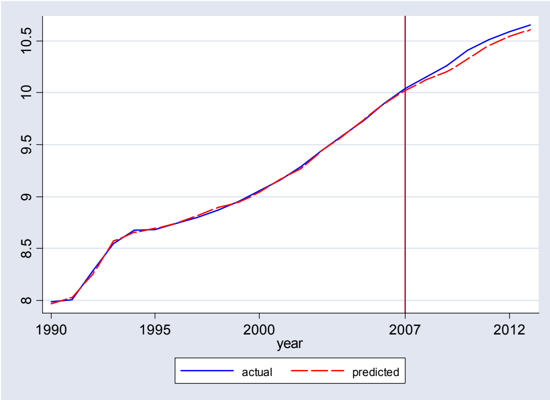


Fig.3. Sensitivity test: Treatment effects in per capita real GDP for the five HSR cities. Notes: 1. In this test, the settings for initial observation for Langfang, Xuzhou and Quanzhou differ from their baseline settings respectively. For Langfang in Hebei province, we set t=1 at 1994 so to add Zhangjiakou and Chengde the two non-HSR cities also from Hebei province to the new control group. For their per capita real GDP fluctuate before 1994. For costal cities Xuzhou and Quanzhou, we set t=1 at 1990 due to the availability of more costal cities in the new control group that also experienced very high growth rate in per capita real GDP e.g. Huzhou, Dongying and Rizhao etc. 2. Data source: China City Statistical Yearbooks, Provincial Statistical Year Books, and China Statistical Year Books. See text for more details.

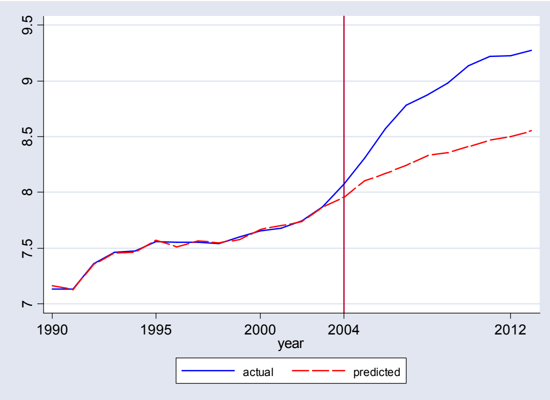
Panel C Changzhou on Hu-Ning Segment

C1: the whole sample period, 1990-2013

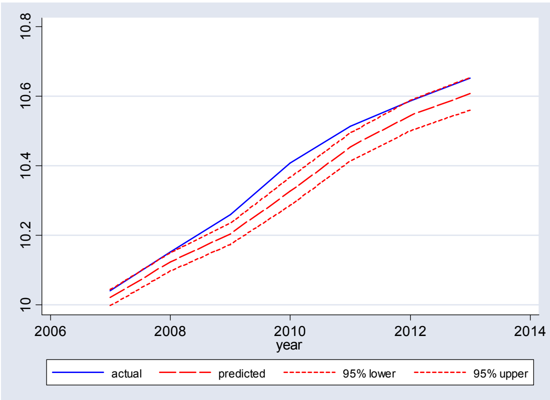


Panel D Qingyuan on Wu-Guang HSR

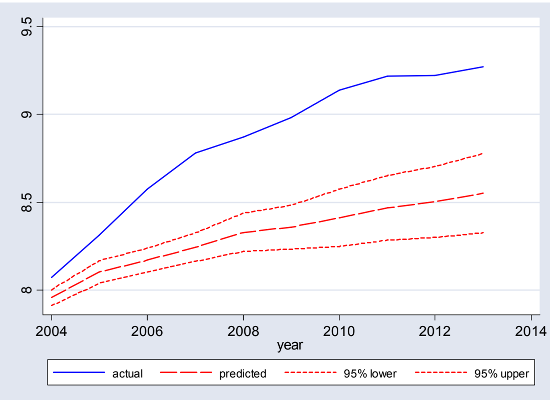
D1: the whole sample period, 1990-2013



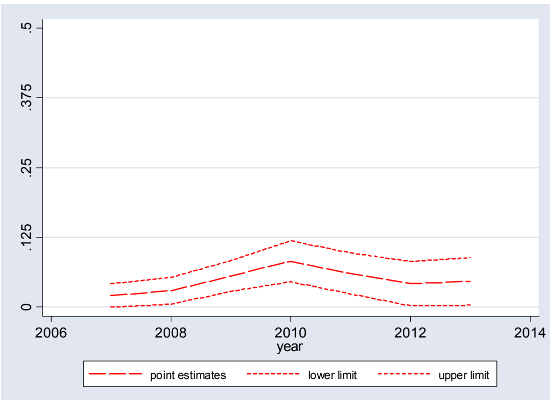
C2: the post-treatment period, 2007-2013



D2: the post-treatment period, 2004-2013



C3: the treatment effects, 2007-2013



D3: the treatment effects, 2004-2013

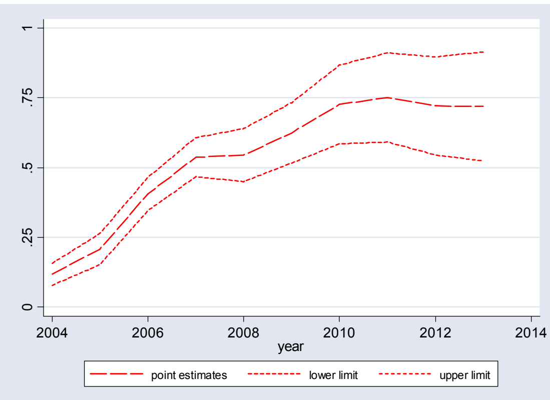
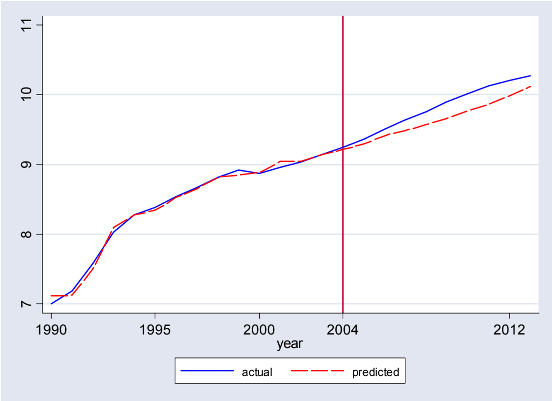
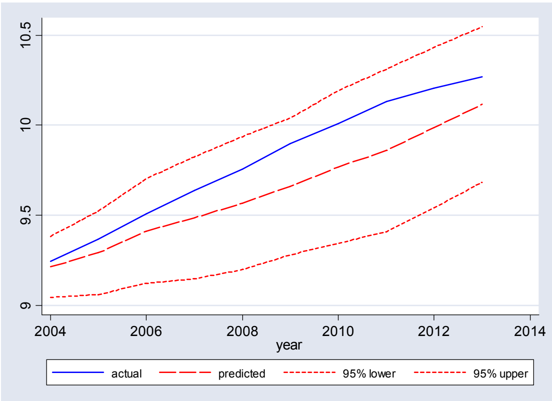


Fig. 3. (*continued*)

Panel E Quanzhou on Yong-Tai-Wen-Fu-Xia Segments
E1: the whole sample period, 1990-2013



E2: the post-treatment period, 2004-2013



E3: the treatment effects, 2004-2013

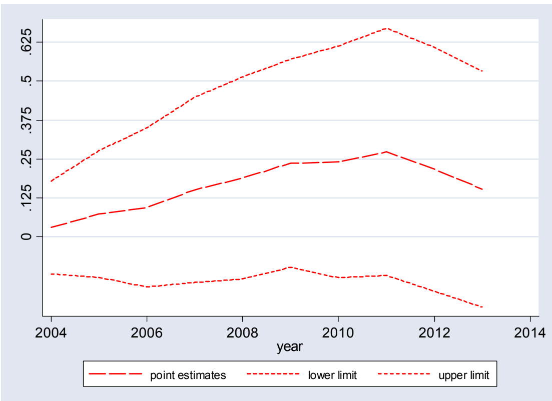


Fig. 3. (*continued*)

estimates of the treatment effects for the baseline results and sensitivity tests overlap during most of the policy evaluation period for Xuzhou and Quanzhou.

In summary, the baseline treatment effects are robust in sign, magnitude, and dynamics during respective policy evaluation periods for most of our HSR cities.

6.2 Refutability test[17]

[17] We follow the idea of Angrist and Krueger (1999) to use refutability test in the consideration of robustness. As a causal model will often yield testable predictions for sub-population in which the "treatment effect" should not be observed because the sub-population did not receive the treatment. Abadie et al., (2010) adopted the similar idea,

To evaluate whether the treatment effects are due to HSR projects or chance, we ran refutability test by applying the method in Hsiao et al. (2012) to every non-HSR city in our baseline control group. In each replication, we treated the individual control group city as if it were an HSR city. In this case, we imposed the HSR treatment with $T_1 + 1$ set in year 2004[18] to one of the 14 control cities and used the rest of the 13 cities as its control group. Also, we chose the best predictors from the 13 control cities using the AICC criterion. If the baseline results for targeted locations are indeed HSR impacts, the difference between actual and hypothetical values of per capita real GDP in log levels for control group cities are seldom significant and the magnitude of the refutability effects for most of the control cities should be much smaller than those of the HSR cities.

Table 10 displays the results for in-sample fit performance and the average impacts during the whole policy evaluation period for the 14 control group cities.

Table 10: Refutability test results

	Pre-intervention		Post-intervention	
Control group city	R-square	F-statistic	ATE	Significance
Wuhai	0.9760	135.49	0.0250	no
Hohhot	0.9979	1407.6	0.0338	no
Zhoushan	0.9991	3211.55	-0.0507	no
Shuangyashan	0.9833	323.47	-0.0485	2004-2007
Chifeng	0.9952	465.4	0.0502	no
Hegang	0.9860	158.27	0.0505	no
Yinchuan	0.9883	365.63	-0.0693	no
Shuizuishan	0.9857	230.37	0.1248	2008-2013
Yancheng	0.9976	922.22	-0.1309	no
Liupanshui	0.9758	134.29	0.1707	no
Tonghua	0.9907	240.83	-0.2071	2004-2007
Baotou	0.9901	225.26	0.2879	no
Jinchang	0.9850	144.04	0.2799	no
Karamay	0.9293	144.2	-0.3659	2009-2013

Notes: 1. ATE is treatment effects averaged over the whole policy evaluation period 2004-2013. 2. We follow the definition for treatment effect significance at 5 per cent level as in the baseline results that actual values of per capital real GDP lie outside of the confidence interval of the predicted counterfactuals for at least four consecutive years in the whole evaluation period. We report the specific periods in which the control group cities have significant refutability impacts. 3. Data source: China City Statistical Yearbooks, Provincial Statistical Year Books, and China Statistical Year Books. See text for more details.

Table 10 shows that all the control group cities have a good in-sample fit with R-square around 0.98 and F-statistic at least above 130, except Karamay[19]. These results suggest the predictive models chosen by AICC have good in-sample performance for the control group as

but the aim is to produce quantitative inference in comparative case studies.

[18] The setting for cut-off period is due to the fact that the 14 cities are also control group for Wuguang HSR line and Yong-Tai-Wen-Fu-Xia Segments that started construction in 2005.

[19] Luckily, AICC did not choose Karamay to be the best predictor for any of our 21 HSR cities. Liupanshui was not chosen by AICC either, thus in the following analysis we consider the 12 control group cities excluding Karamay and Liupanshui.

well, so that we can compare the refutability impacts with the baseline results for HSR cities in Table 4.

Among the 12 control cities, for the post-treatment period, seven of them have positive refutability ATEs and the other five are negative. Moreover, as expected, we did not find a statistically significant refutability impact for most of the control group cities, with the exceptions of Shuangyashan, Shizuishan, and Tonghua.

Recall that in Section 4 we found that 10 out of the 21 HSR cities had statistically significant effects for at least four consecutive years during the whole evaluation period. To compare the magnitude of the refutability ATEs for the 12 control cities with ATEs estimated for the 10 HSR cities with significant treatment effects, we show their distribution in Fig.4.

Fig.4. Comparisons between treatment and control groups in post-treatment average effects. Notes: The two figures show the histogram and kernel density of the magnitude of the difference between actual and hypothetical per capita real GDP for the 10 HSR cities with significant treatment effects and for the 12 control group cities respectively.

Fig. 4 suggests that the distribution of the magnitude for the HSR impacts was more dispersed than that of the refutability impacts. For the HSR cities in our treatment group, the sizes of impact concentrate in range between 10% and 20%, while, for the control group, the sizes of refutability impact concentrate between 2.5% and 5%. The results indicate that the magnitudes of the estimated average impacts for most of the HSR cities are much larger than those of the control group cities, which is consistent with our expectation.

To conclude, we found little evidence that the refutability tests for our control group cities had perceivable effect.

7. Conclusion

This paper has examined how China's recently completed Four Vertical HSR projects have influenced local economic growth in targeted city nodes. We found substantial heterogeneous effects in per capita real GDP across targeted city nodes, in the sense that the impacts differed by location, route, and region. We found that HSR projects have significantly and continuously raised the per capita GDP for 48% of the treatment group cities we studied. The size of their impact is economically important and in some cases huge: ranging between a minimum of 5% increase for Zhenjiang on the Hu-Ning Segment and a maximum of 59% for Qingyuan on the Wu-Guang HSR. Two robustness tests were conducted that strongly suggest that our baseline estimation results are robust with respect to the selection of control groups.

By using the method described in Hsiao et al. (2012), we were able to take into account the potential location-level heterogeneous responses to the newly constructed HSR projects by examining individual targeted cities along the HSR lines/segments. Also, we could analyze the spatial distribution of HSR impacts at various spatial scales. The methodology in Hsiao et al. (2012) is particularly useful when policy makers and researchers are not only interested in the single value of ATE for the whole population or the subsample of unintended peripheral units but are also interested in the responses of HSR-targeted cities at the individual location level over time. It could work as an informative complementary approach to the widely used IV-2SLS estimator in transportation literature, especially in testing the existence and estimating the extent of treatment effects heterogeneity at the location level.

We found that HSR cities with positive ATEs concentrated along the Hu-Ning Segment, the Yong-Tai-Wen-Fu-Xia Segment, and within the Hunan province along the Wu-Guang HSR. At the regional level, we found that most targeted locations receiving positive impacts spatially agglomerate on the east coast of China, all concentrated in core urban clusters, such as the Yangtze River Delta, the West Coast of the Straits, and the Chang-Zhu-Tan area in the Hunan province. Furthermore, they are usually transportation hubs. Additional analysis indicates that the gain on the local economy is greater for cities that are more industrialized, with more ability of the service sector to employ labor, and with better supporting infrastructure. During the construction period, larger cities tend to gain. When the HSR projects open to public, locations with more capacity for the service sector to create jobs and those with more human capital and tourist attractions tended to gain more from HSR projects. Importantly, we found local protectionism could significantly hamper the development of HSR cities.

Our main findings about what can help or hamper development in HSR cities can be useful for policy makers. For local governments of HSR cities without natural location advantages, one might need to pay more attention to location-based policy, e.g., improving both “hard” and “soft” supporting infrastructure. For cities still competing to acquire an HSR project, local governments should be clear about whether the level of economic activity will receive positive effects by HSR projects, especially in the short run.

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References

Abadie. A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: estimating the effect of California's tobacco control program. *Journal of the American Statistical Association*, 105(490), 493-505.

Ahlfeldt, G.M., & Feddersen, A. (2010). From periphery to core: Economic adjustments to high speed rail. *Working paper.* London School of Economics.

Angrist, J.D., & Krueger, A.B. (1999). Empirical strategies in labor economics. In: Ashenfelter, A., Card, D. (Eds.), *Handbook of Labor Economics*, vol. 3. Elsevier, Amsterdam. 1277-1366.

Bai, C.E., Ouyang, M., & Li, Q. (2014). Property taxes and home prices: A tale of two cities. *Journal of Econometrics*, 180(1), 1-15.

Banerjee, A., Duflo, E., & Qian, N. (2012). On the road: Access to transportation infrastructure and economic growth in China. *Working paper.* National Bureau of Economic Research.

Baum-Snow, N. (2007). Did highways cause suburbanization? *The Quarterly Journal of Economics*, 122(2), 775-805.

Baum-Snow, N., Brandt, L., Henderson, J.V., Turner, M.A., & Zhang, Q.H. (2015a). Roads, railroads and decentralization of Chinese cities. *Working paper*. Brown University.

Baum-Snow, N., Brandt, L., Henderson, J.V., Turner, M.A., & Zhang, Q.H. (2015b). Transportation infrastructure, urban growth and market access in China. *Working paper*. Brown University.

Behrens, K., & Robert-Nicoud, F. (2015). Agglomeration Theory with Heterogeneous Agents. In: Duranton, G., Strange, W., Henderson, V. (Eds.), *Handbook of Regional and Urban Economics*, vol. 5. Elsevier, Amsterdam, 171-245.

Bleakley, H., & Lin, J. (2012). Portage and path dependence. *The Quarterly Journal of Economics*. 127(2), 587–644.

Casaburi, L., Glennerster, R., & Suri, T. (2013). Rural roads and intermediated trade: Regression discontinuity evidence from Sierra Leone. *Working paper.* National Bureau of Economic Research.

Chandra, A., & Thompson, E. (2000). Does public infrastructure affect economic activity?: Evidence from the rural interstate highway system. *Regional Science and Urban Economics,* 30(4), 457–490.

China Railway Corporation. (2016). Construction work conference. http://www.china-railway.com.cn/xwdt/jrtt/201601/t20160127_55113.html

Ching, H.S., Hsiao, C., & Wan, S.K. (2012). Impact of CEPA on the labor market of Hong Kong. *China Economic Review*, 23(4), 976-981.

Donaldson, D. (2015). Railroads of the Raj: Estimating the impact of transportation infrastructure. *American Economic Review*, forthcoming.

Duranton, G., & Turner, M.A. (2012). Urban growth and transportation. *Review of Economic Studies*, 79(4), 1407-1440.

Ellison, G., & Glaeser, E.L.(1999). The geographic concentration of industry: does natural advantage explain agglomeration? *The American Economic Review Papers and Proceeding*, 89(2), 311–316.

Faber, B. (2014). Trade integration, market Size and industrialization: Evidence from China's national trunk highway system. *Review of Economic Studies*, 81(3), 1046-1070.

Fernald, J.G. (1999). Roads to prosperity? Assessing the link between public capital and productivity. *The American Economic Review*, 89(3), 619-638.

Fujita, M., Krugman, P., & Venables, A.J. (1999). *The spatial economy: cities, regions and international trade*. Hoboken, NJ: Wiley.

Guirao, B., & Campa, J. L. (2015). The effects of tourism on HSR: Spanish empirical evidence derived from a multi-criteria corridor selection methodology. *Journal of Transportation Geography*, 47, 37-46.

Heckman, J.J. (1979). Sample selection bias as a specification error. *Econometrica*, 47(1), 153-161.

Heckman, J.J. (1997). Instrumental variables: A study of implicit behavioral assumptions used in making program evaluations. *Journal of Human Resources*, 32(3), 441-462.

Heckman, J.J. & Vytlacil, E.J. (2001). Local instrumental variables. In: Hsiao, C., Morimune, K., & Powell, J.L. (Eds.). *Nonlinear statistical modeling*. Cambridge, UK: Cambridge University Press, 1-46.

Hsiao, C., Ching, H.S., & Wan, S.K. (2012). A panel data approach for program evaluation—Measuring the benefits of political and economic integration of Hong Kong with mainland China. *Journal of Applied Econometrics*, 27(5), 705-740.

Hsiao C. (2014). *Analysis of Panel data* (3rd ed.). Cambridge: Cambridge University Press.

Hurvich, C.M., & Tsai, C.L. (1989). Regression and time series model selection in small samples. *Biometrika*, 76(2), 297-307.

Li, J.W. (2000). *Railway and development.* Beijing: Social Science Literature Press (in Chinese).

Lin, Y.T. (2014). Travel costs and labor market integration: Evidence from China's high speed railway. *Working paper.* London School of Economics.

Marti-Hennenberg, J. (2000). Un balance del tren de alta velocidad en Francia. Enseaszas para el caso Espaol. *Eria*, 52(3), 131-143.

National Railway Administration of the People's Republic of China. 2016. http://www.nra.gov.cn/fwyd/hyjc/zggstlzt/zggstl1/dtsz/201510/t20151022_18206.html

Redding, S.J., & Turner, M.A.(2015). Transportation costs and the spatial organization of economic activity. In: Duranton, G., Strange, W., Henderson, V.(Eds.), *Handbook of Regional and Urban Economics*, vol. 5. Elsevier, Amsterdam, 1339-1398.

Rosenbaum, P., & Rubin, D.B. (1983). The central role of propensity score in observational studies for causal effects. *Biometrica*, 70 (1), 41-55.

Sasaki, K., Ohashi, T., & Ando, A. (1997). High-speed rail transit impact on regional systems: Does the Shinkansen contribute to dispersion? *The Annals of Regional Science,* 31(1), 77-98.

State Council (2008): Mid-to-Long Railway Plan (2008 adjusted). http://www.sdpc.gov.cn/zcfb/zcfbqt/200906/t20090605_284525.html.

Urena, J.M., Menerault, P., & Garmendia, M. (2009). The high-speed rail challenge for big intermediate cities: A national, regional and local perspective. *Cities*, 26(5), 266-279.

Van de Walle, D., & Mu. R. (2007). Fungibility and the flypaper effect of project aid: micro-evidence for Vietnam, *Journal of Development Economics*, 84(2), 667-685.

Van de Walle, D. (2009). Impact evaluation of rural road projects. *Journal of Development Effectiveness*, 1(1), 15-36.

Vickerman, R., & Ulied, A. (2006). Indirect and wider economic impacts of High-Speed-Rail. In: G. de Rus, (Eds.). *Economic Analysis of High Speed Rail in Europe*, Madrid, Spain: Fundacion BBVA, 89-103.

Yao, Y. (2014). The Chinese Growth Miracle. In: Aghion, P., Durlauf, S.N. (Eds.), *Handbook of Economic Growth*, vol. 2b. Elsevier, Amsterdam. 943-1031.

Zheng, S.Q., & Kahn, M.E. (2013). China's bullet trains facilitate market integration and mitigate the cost of megacity growth. *Proceedings of the National Academy of Sciences*, 110(14), 1248-1253.