**UNIVERSITY OF WAIKATO**

**Hamilton**
**New Zealand**

# Local economic effects of connecting to China's high-speed rail network: Evidence from spatial econometric models

Xiaoxuan Zhang, and John Gibson

**Working Paper in Economics 3/24**

June 2024

**Xiaoxuan Zhang**
University of Waikato

*Corresponding Author*

**John Gibson**
School of Accounting, Finance
and Economics
University of Waikato
Private Bag 3105
Hamilton, 3240
New Zealand

Tel: +64 (7) 838 4289
Email: jkgibson@waikato.ac.nz

## Abstract

China's high-speed rail (HSR) has quickly expanded to over 40,000 km of lines operating and another 10,000 km under construction. This is over 10-times longer than the networks in long-established HSR countries like France, Germany or Japan. While fewer than 100 county-level units had stations on the HSR network in the first years of operation, the eight years from 2012-19 saw almost 400 more county-level units connect to the HSR network. Effects on local economic activity from this substantial increase in connections to the HSR network remain contested. Some prior studies find either insignificant effects on local economic growth or even negative effects in peripheral regions. In light of this debate, we use spatial econometric models for a panel for almost 2500 county-level units to study effects of connecting to the HSR network. We especially concentrate on the 2012-19 period that has high quality night-time lights data to provide an alternative to GDP as an indicator of growth in local economic activity. Our spatial econometric models allow for spatial lags of the outcomes, of the covariates, and of the errors. We also address potential endogeneity of the HSR networks and connections, using an instrumental variables strategy. Across a range of specifications, we generally find that growth in local economic activity is lower following connection to the HSR network, with this effect especially apparent when using high quality night-time lights data for the 2012-19 period. Hence, expansion of the HSR network may not boost China's economic growth.

**JEL Codes**

R12

**Keywords**

High-speed rail
infrastructure
luminosity
spatial spillovers
China

**Acknowledgements**

Financial support from the Marsden Fund project UOW1901.

# I. Introduction

Transportation infrastructure is generally regarded as a key driver of regional economic growth and development (Ma, Chen, and Yang 2020; Egger, Loumeau, and Loumeau 2023). High-speed rail (HSR) is a significant transport innovation (Wang, Jiang, and Miao 2023; Li, Yu, and Ma 2024), with advantages of speed, efficiency, energy saving, safety, punctuality, and stability (Li et al. 2021; Wang et al. 2023; Liu, Diao, and Lu 2024). Since the first HSR route opened in Japan in 1964, more than 20 countries have commenced HSR operations (Wang et al. 2024). Although China was a latecomer to HSR construction, it has developed extremely fast (Mei, and Zhang, 2021). Starting with the opening of the Beijing-Tianjin intercity HSR in 2008, China developed the world's longest HSR network with the highest transportation density (Banerjee et al. 2020; Wang, Jiang, and Miao 2023; Tang et al. 2024). According to the State Council Information Office, China's HSR network exceeded 43,700 km by the end of November 2023, which ranks first in the world (Ren et al. 2024). In addition, China's HSR network is still expanding. The China National Railway Group Limited stated that China's railway network will eventually span approximately 200,000 kilometers, including about 70,000 kilometers of HSR, by 2035 (Li and Li, 2024).

A growing literature studies local economic development impacts of HSR networks. For example, Ahlfeldt and Feddersen (2018) find that HSR stimulated the economic vitality of cities in Germany. Carbo et al. (2019) studied economic effects of HSR in Spain from 1995 to 2014 using difference-in-differences (DID) and found positive effects on urban economies. Based on a Computable General Equilibrium (CGE) model, Kim and Yi (2019) found that HSR benefitted Gross Regional Product (GRP) growth in South Korea. Likewise, positive effects of HSR on economic activity are found in studies from Italy (Cascetta et al., 2020), France (Facchinetti-Mannone, 2019) and Japan (Miwa, Bhatt, and Kato, 2022).

For China, scholars have used various methods to study HSR impacts in different regions. The empirical evidence on impacts tends to be mixed. Most studies show significant positive economic effects on cities along HSR routes. For example, using DID, Diao (2018) and Wang et al. (2022) found HSR had a positive role in promoting provincial economies by increasing GDP and accessibility. With a CGE model, Yang et al. (2023) found that HSR could stimulate GDP growth and reduce regional disparities in eastern China. Relatedly, Jin et al. (2024) focus on accessibility and connectivity features of HSR, and the role of the HSR network in alleviating urban–rural income disparity. Li and Li (2024) find that the opening of HSR lines positively stimulates economic growth, primarily through market size.

However, some researchers have found that HSR may have negative economic effects. For example, Qin (2017) found that GDP of counties along China's HSR routes are reduced by 3%-5% on average, with this decline operating through decreased fixed asset investments. Using a DID model, Gao et al. (2020) estimate a long-lasting negative effect of HSR on GDP per capita within the Yangtze River Delta region, of approximately 10%, mainly due to the population reallocation. Liu et al. (2022) found that large scale inter-regional HSR reduced labor productivity by almost 13% and the productivity gap between central and peripheral cities in the network widened after connecting to the HSR network.

Despite this growing body of empirical research, a key aspect of the potential impact on local economic activity from connecting to the HSR network remains largely unexamined. Most previous studies only explore the direct impact of HSR opening on regional economic development. This may be insufficient given that transport infrastructure, and especially HSR, shortens travel time and improves inter-city accessibility, and thus contributes to the flow of capital, ideas, population, and other factors between cities (Shi, and Wang, 2024). Consequently, the effects induced by transport infrastructure are likely to extend to the neighbouring areas. These spillovers are often ignored in applied studies, which use impact evaluation frameworks that treat the spatial units as independent of their surrounding areas. Hence, the results from prior studies may not represent the complete impacts if these spatial spillover effects are not considered.

To overcome this gap in the literature, the current study uses a comprehensive set of spatial econometric models to examine the impacts that connecting to the HSR network has on local economic activity. We use a decade-long panel of almost 2500 county-level units in China to examine HSR impacts on GDP and on luminosity as indicators of local economic activity. The research framework not only considers the spillover effects of connecting to the HSR network but also allows for the endogenous placement of HSR routes. In comparison to much of the existing research, our focus is on economic activity at a more local level, but with our sample covering almost all of China. Second, previous studies often use the DID model to test the impacts of HSR operation but do not consider spatial factors such as spillovers. In contrast, spatial spillover effects of HSR can be captured with spatial econometric models. In our framework, we start with a very general spatial autoregressive model with spatial autoregressive errors (SARAR) that encompasses popular models like the spatial Durbin model, the spatial lag model, and the spatial error model. Lastly, by using an instrumental variables (IV) strategy, we can assess whether the endogenous placement issue interferes with estimation of the impact of HSR on the regional economy. Our analysis not only advances the understanding of how HSR affects economic growth at the county level in China but also provides insight into the planning of future HSR networks.

The subsequent parts of the paper are structured as follows. Section 2 reviews the literature related to HSR and discusses the main contribution of the study. Section 3 describes the data used in this study and the econometric modelling framework, including the spatial econometric models, and the instrumental variables strategy used to allow for the endogenous placement of HSR. Section 4 presents the empirical results, using both county-level GDP and night-time lights as indicators of economic activity. Finally, Section 5 concludes the study, and discusses the limitations.

## II. Literature review

In this section, we review literature on the impact of high-speed rail (HSR) on local economic development in China. We focus especially on the empirical methods and the indicators of local economic activity. The reviewed studies cover a wide range of topical issues, including whether to take into account the spatial econometric models and the HSR endogenous placement issues.

Rail transport is a crucial mode of inter-region transportation in China, a large developing country with a widespread geographical distribution of natural resources and population (Ke et al. 2017). HSR has become the fastest-growing transportation mode in China due to the advantages of efficiency, punctuality, and stability (Xu, and Huang, 2019; Tian et al., 2021). As a result of the rapid development, research on the impacts of HSR networks has become a hot topic in China (Luan, Guo, and Liang, 2024). However, the impact of HSR on the regional economic development of peripheral cities along its line is still under debate. Researchers use a variety of spatial scales for these studies, and different conclusions concerning the promotion, inhibition, or insignificance of HSR on local economic growth have been reported.

Studies of the impact of HSR on regional economic growth (both within and beyond China) are mostly based on methods such as the synthetic control method (Albalate, Campos, and Jiménez, 2023), computable general equilibrium (CGE) model (Kim and Yi, 2019), and difference-in-differences (DID) model (Chen, Lv, and Zhang, 2024). For example, Yu et al. (2021) applied the synthetic control method and found that HSR raises a county's total GDP.

Using a dynamic CGE model, Chen (2019) found that HSR infrastructure development in China has generated a positive regional economic impact. Compared to the above methods, the DID model has been used more broadly to investigate HSR's impacts on socioeconomic conditions. For example, Chen et al. (2023), and Liang et al. (2020) used county-level panel data to study the economic impacts of HSR, which showed that the opening of HSR led to economic growth along the route. Wang et al. (2023) used GDP data to investigate the heterogeneous economic effects of HSR on prefecture-level cities. In addition to GDP, nighttime lights data are recognized as an effective proxy index related to human activities and urban economic development. Guo et al. (2023) adopted nighttime light data as a proxy for regional economic activity and found that HSR had a positive impact.

Considering that transport infrastructure in a region not only affects local economic growth but also economic activities in adjacent areas, some studies used spatial econometric models to examine the aggregate growth effect and potential spatial spillover effect of HSR. Liu, Tang, and Wang (2024) showed that the construction of HSR led to a notable increase in income through a positive spatial spillover effect. Based on the Spatial Durbin model (SDM), Sun et al. (2023) and Huang (2021) analyzed the direct and indirect effects of HSR on economic development. However, not all uses of these models find positive economic spillovers for regional economic development. Jin et al. (2020) found that the spillover effect is insignificant based on the SDM model.

The selection of high-speed rail stations is usually considered to be non-random and biased towards cities with better economic development. Given these endogeneity issues, many studies used an Instrumental variables (IV) strategy. To construct an IV for actual HSR connections, previous studies either referred to historical information or used the straight-line strategy. Historical transport routes were mainly located based on the original local geological conditions due to the then-technical restrictions, and the original geological conditions were highly related to the construction of transportation infrastructure, such as for post-cities. Hence, post-cities from the Ming Dynasty (1368—1644) were chosen as the instrumental variables for transportation infrastructure in the regression models of Guan, Chen, and Li (2023), and Wang, Jiang, and Miao (2023). Similar practices are followed by Chen, Cheng, and Zhang (2023), and Guo et al. (2021), who used China's historical transportation network in 1961 as the IV for the current HSR connections.

In contrast to the historical instruments, the straight-line strategy is based on connecting large central cities, using the shortest distance (which should also result in fastest journeys notwithstanding potentially higher construction costs). The instrumental variable obtained by the minimum spanning tree should be highly relevant to the actual HSR line and thus is used to construct IVs for the actual transport connection. For example, Qiu, Liu, and Liao (2023), and An et al. (2022) constructed an IV by drawing straight lines among major cities, to predict the location of the current HSR connection. Shen, Li, and Li (2023), and Chong, Chen, and Qin (2019) used both the spatial econometric model and an IV strategy to explore the economic impacts of HSR, finding that the impacts were not significant.

To help summarize this large and growing literature on the impacts of HSR on regional economic activity in China, 30 recent studies are described classifying them along two dimensions: whether they allow for or ignore spatial spillovers and whether they treat the placement of the HSR networks as endogenous or exogenous (Table 1). Despite broad discussions about the effects of HSR connection on regional economic development, it can be seen that the spillover effects of HSR have received inadequate attention, with far more studies in Table 1 ignoring spillovers (n=23) than allowing for spillovers (n=7). The combination of allowing for spillovers and allowing for endogenous placement is very rare (n=2). Our paper adds to this small literature because we consider both of these issues in our econometric models.

In summary, existing studies on the economic impact of high-speed rail have not yet reached consistent conclusions, perhaps due to the differences in their spatial scope and research methods. In terms of spatial scale, there is little systematic research focused on the county-level economic impacts. Most of the previous HSR impact studies are based on panel data from provinces or prefectural cities, while panel data from county-level areas are less commonly used. This paper aims to address these gaps.

Table.1 Selected studies analyzing HSR impacts

| Authors | Year | Time period | Spatial units | Spatial approach | IV approaches | Indicator(s) | Result | Objective |
|---|---|---|---|---|---|---|---|---|
| *Panel A: Studies that assume exogenous placement and no spatial spillovers* | | | | | | | | |
| Chen et al. | 2023 | 2008-2017 | 328 counties | / | / | GDP | +ve | To assess impacts of HSR opening on the inter-county economic gap |
| Wang, Yu, and Zhang | 2023 | 1999-2013 | 333 prefectures | / | / | GDP | +ve | To find the heterogeneous economic effects of distance to HSR |
| Wang et al. | 2023 | 2007-2018 | 62 prefecture-level cities | / | / | GDP | +ve | To estimate direct impacts of opening HSR on regional economic development |
| Yu et al. | 2021 | 2001-2017 | 54 counties in Hubei Province | / | / | GDP | +ve | To analyse impacts of HSR on economic growth |
| Guo et al. | 2020 | 2002-2018 | 24 cities | / | / | Luminosity | +ve | To investigated the impact of the HSR on urban economic development using NTL |
| Li, Wu, and Zhao | 2020 | 2001-2017 | 40 prefecture-level cities | / | / | GDP | +ve | To investigate the economic effect of HSR |
| Liang et al. | 2020 | 2012-2017 | 632 counties | / | / | GDP | +ve | To explore impacts of HSR on economic growth along the route |
| Chen | 2019 | 2002-2013 | | / | / | GDP | +ve | To access the regional economic impacts of HSR |
| *Panel B: Studies that assume exogenous placement but allow for potential spatial spillovers* | | | | | | | | |
| Liu, Tang, and Wang | 2024 | 2000-2018 | 286 prefecture-level cities | SDM | / | Income | +ve | To investigate the impact of HSR on urban residents' income |
| Sun et al. | 2023 | 2003-2018 | 285 prefecture-level cities | SDM | / | GDP | +ve | To examine joint impacts of HSR on the urban economy |
| Huang | 2021 | 2008-2018 | 281 cities | SDM | / | GDP | +ve | To discuss the spatial–temporal heterogeneity of the relationship between HSR and the urban economy |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Yu | 2021 | 2005-2013 | 47 prefecture-level cities | SDID | / | GDP | +ve | To investigate the influence of Beijing-Shanghai HSR on regional economy |
| Jin et al. | 2020 | 2002-2016 | 285 cities | SDM | / | GDP | +ve | To examine the role of HSR in influencing economic growth and disparity |
| *Panel C: Studies that allow for endogenous placement but do not allow for potential spatial spillovers* | | | | | | | | |
| Chen, Cheng, and Zhang | 2023 | 2003-2014 | 351 cities | / | 1961 train station | GDP | +ve | To study the effects of HSR construction on firms' cross-regional development |
| Guan et al. | 2023 | 2011-2019 | 41 cities in YRD region | / | Ming Dynasty post station | GDP | +ve | To test the impact of HSR on high-quality economic development |
| Qiu, Liu, and Liao | 2023 | 2003-2019 | 284 prefecture-level cities | / | Straight lines | GDP | +ve | To investigate the impact of railway express on urban carbon emissions reduction |
| Wang, Jiang, and Miao | 2023 | 2003-2019 | 277 prefecture-level cities | / | Courier roads in the Ming Dynasty | GDP | +ve | To examine HSR's impact on urban resilience |
| Wang, Zhou, and Guo | 2023 | 2010-2018 | 34 prefecture level cities | / | Railway stations in 1993 | Urban tourism incomes | +ve | To explore the spatial impact of HSR on tourism economy |
| Yang and Ma | 2023 | 2001-2020 | 285 cities | / | Railway stations in 1912s | GDP | +ve | To study the impact of the border effect on HSR links |
| An et al. | 2022 | 2005-2018 | 40 prefecture cities in YRD region | / | Straight lines | GDP | +ve | To investigate the effects of HSR on local economic development |
| Chen and Wang | 2022 | 2003-2019 | 291 prefecture-level cities | / | Straight lines | GDP | +ve | To study the impact of HSR on the consumer service industry |
| Liu et al. | 2022 | 2001-2015 | 236 prefecture-level cities | / | Straight lines | GDP | -ve | To explore effects of HSR on labor productivity |
| Wang, Wu, and Liu | 2022 | 2001-2016 | 219 prefecture-level cities | / | Straight lines | GDP | +ve | To explore effects of HSR connection on urban innovation |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Dong et al. | 2021 | 2000-2020 | 180 towns | / | Straight lines | GDP | +ve | To explores the determinants of HSR new towns' economic growth |
| Guo et al. | 2021 | 2004-2010 | 20 cities | / | 1961 China railway map | GDP | +ve | To investigate the impact of HSR on regional water environment |
| Kuang, Liu, and Zhu | 2021 | 2004-2017 | 141 cities | / | 1962 China railway map | GDP | +ve | To study the relationship between HSR connection and firm performance |
| Gao et al. | 2020 | 2006-2015 | 211 county-level units in YRD region | / | Straight lines | GDP | -ve | To investigate effects of connecting to an HSR line on the local economy |
| Yao et al. | 2019 | 2010-2014 | 285 cities | / | China's historical railway network | GDP | +ve | To study the HSR impacts on economic growth |
| *Panel D: Studies that allow for endogenous placement and also allow for potential spatial spillovers* | | | | | | | | |
| Shen, Li, and Li | 2023 | 2011-2020 | 229 cities | GS2SLS | The post cities in the Ming Dynasty | GDP | ns | To study the influence of transportation infrastructure on digital economy |
| Chong, Chen and Qin | 2019 | 2008-2015 | 268 cities | SAR, SEM, SDM | Historical routes | GDP | +ve | To evaluate the economic benefits of HSR network from the perspective of connectivity improvement |

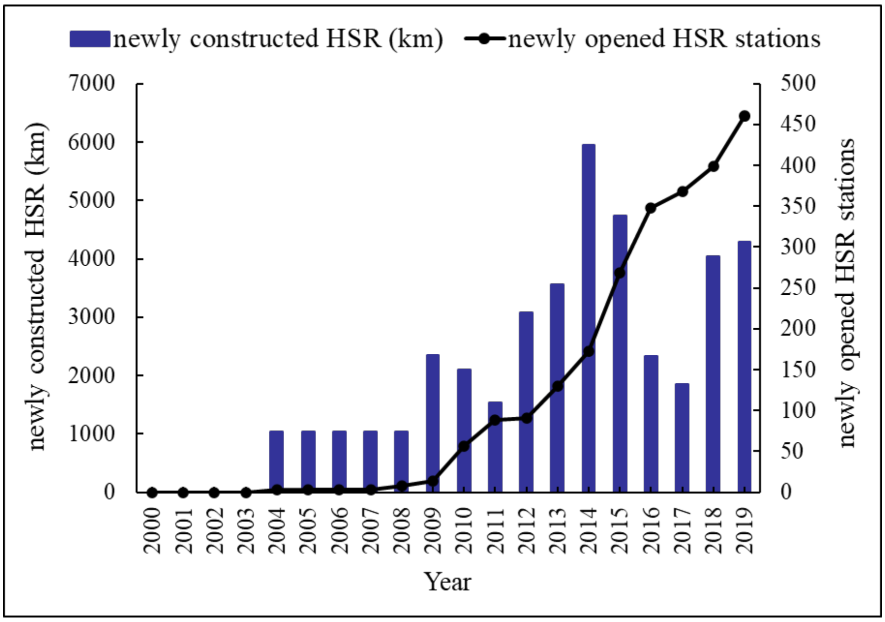
*Notes*: Abbreviations for spatial approach: GS2SLS (generalized spatial two stage least squares), SAR (spatial autoregressive model), SDM (spatial Durbin model), SEM (spatial error model), SDID (spatial difference-in-differences); +ve refers to positive effects, -ve refers to negative effects, ns refers to insignificant effects.

## III. Data and Methods

*Data Sources*

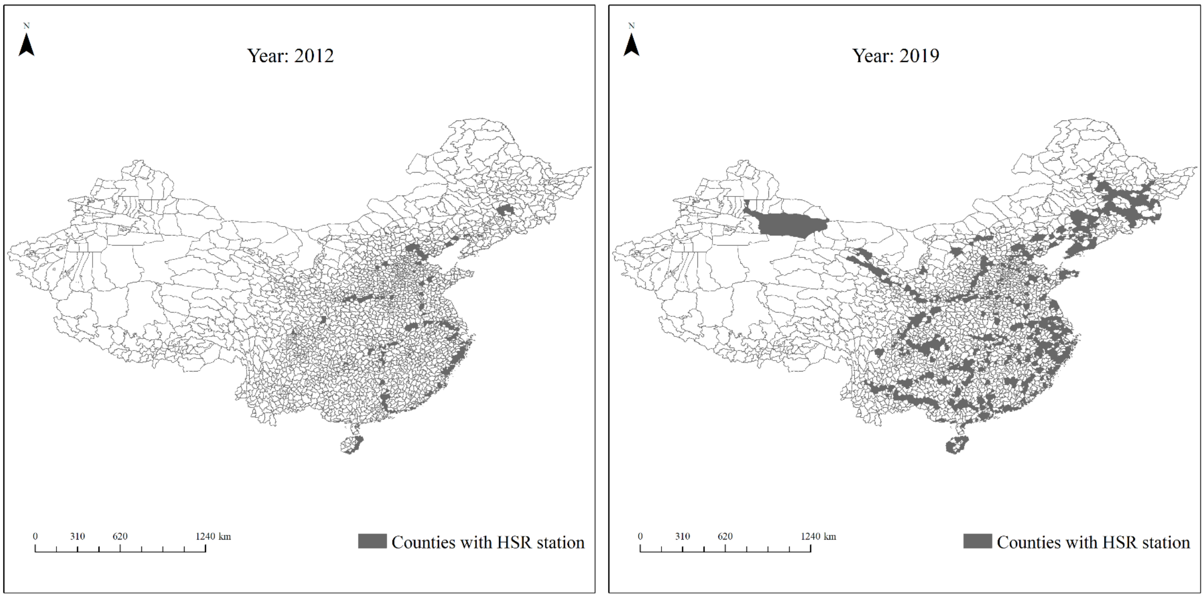
High-speed rail refers to high-speed trains with a design speed of over 250 km/h or passenger dedicated intercity lines with an average speed of 200 km/h or more. The HSR data were manually collected and include information such as the opening dates of each of China's HSR corridors in operation by the end of 2019, and the new length for each year. The sources for high-speed rail data include the National Railway Corporation (www.china-railway.com.cn) and the 12306 China Railway (http://www.12306.cn). For stations opening later than July 1 in a year, the opening date is set as the next year (the dummy variable HSRopen = 1). The development of HSR in China began with the opening of the first HSR line at the end of 2008. Since then, the HSR network has experienced rapid expansion, particularly starting from 2012 (as shown in Fig. 1). Thus we adopt the research period from 2012 to 2019 (which also coincides with the availability of high quality luminosity data). During the research period, a total of 460 counties (out of 2342 counties in all of China) had HSR stations opened. The spatial distribution of HSR stations in China in 2012 and in 2019 is shown in Fig. 2. The expansion westwards, and to the northeast, and the increased density in central and southeast China is evident.

**Figure 1.** The growth of China's high-speed rail (HSR) network




Note: The data are sourced from the National Railway Administration of the people of China (http://www.nra.gov.cn) and National Bureau of Statistics (www.stats.gov.cn)

**Figure 2.** HSR stations in China as of 2012, and 2019




Note: The darkest areas, which take the value of 1 in the econometric models, are the counties and districts connected by HSR lines; the areas taking the value of 0 are counties and districts not connected by HSR lines.

To empirically analyze impacts we use two measures of local economic activity—GDP and luminosity. The GDP data were obtained from three main products of the National Bureau of Statistics (NBS): (i) annual editions of the China Statistical Yearbook (county-level) (in Chinese it is *Zhongguo Xianyu Tongji Nianjian* (*Xianshi Juan*)), (ii) annual editions of the China City Statistical Yearbook (known as *Zhongguo Chengshi Tongji Nianjian*), and (iii) annual editions of the Statistical Yearbook for each city or province (for example, the Beijing Statistical Yearbook) (NBS, various dates). Each edition reports on GDP the previous year, so we use the 2013 to 2020 editions to obtain annual GDP data from 2012 to 2019. Overall, we have a balanced panel of annual GDP data for each of n = 2342 units at the 3rd level of the sub-national administrative hierarchy, where these units maintain a consistent spatial definition from 2012 to 2019.

The luminosity data we select to represent the level of regional economic growth are the annual composites from Defense Meteorological Satellite Program (DMSP) satellites and from the Visible Infrared Imaging Radiometer Suite (VIIRS) from the Suomi-NPP satellites. The DMSP annual composites from satellites F15 and F18 collectively cover each year from 2012 to 2019. The stable lights product provides 6-bit digital numbers (DN) from 0–63 for each 30 arc-second output pixel (approximate 1.04 km×1.04 km at China's latitude). Ephemeral lights, such as from fires and flaring, are removed and processing excludes (at pixel level) images for nights affected by clouds, moonlight, sunlight, and other glare. The VIIRS data we used is the version 2.1 VIIRS Day/Night Band nighttime lights (VNL), which are available beginning in 2012. The VNL is produced from monthly cloud-free radiance averages, with initial filtering to remove extraneous features such as fires and aurora before the resulting rough annual composites are subjected to outlier removal procedures (Elvidge et al., 2021). The data are in units of nano Watts per square centimeter per steradian ($nW/cm^2/sr$) reported on a 15 arc-second output grid (approximate 0.52 km×0.52 km). We mainly use the average masked data product with background noise, biomass burning, and aurora zeroed out, which had the highest predictive power for GDP amongst all of the VNL data products in a prior study at the same county-level resolution that the current study uses (Zhang, and Gibson, 2022). Our constructed panel dataset contains annual observations for 2342 county-level units (which includes districts, county-level cities and counties) in China from 2012 to 2019. Table 2 shows the descriptive statistics.

Table 2. Descriptive statistics of variables

| Variable | Sample size | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| HSRopen | 18736 | 0.119 | 0.324 | 0 | 1 |
| lGDP | 18736 | 4.883 | 1.284 | 0.262 | 10.508 |
| lDMSP | 18736 | 8.400 | 1.353 | 0 | 12.829 |
| lVNL | 18736 | 8.017 | 1.329 | 1.816 | 13.214 |

Notes: Statistics are for n=2342 spatial units, annually observed in a balanced panel from 2012 to 2019.

*Estimation Framework*

Spatial econometric models let us examine the nature of possible spillovers, and are used for this purpose in many contexts (LeSage and Pace, 2009). A key aspect of these models aiding the study of spillovers is that possible interactions between spatial units are summarized with a $N \times N$ spatial weights matrix, $W$. In this study we use a row normalized contiguity weights matrix that has values of one for neighbours and zero otherwise, with a diagonal of zeros because a spatial unit cannot neighbour itself. At the level of spatial disaggregation that we use, the average spatial unit in China has six neighbours.

In what follows, the proxy for economic output in spatial area $i$ in year $t$ is denoted as $O_{it}$, where the two proxy variables we use are log GDP in our main specification, and the log of the sum of night-time lights in our sensitivity analysis. The indicator for whether a spatial unit has a HSR station is $D_{it}$ the $\mu_i$ are time-invariant fixed effects for each spatial unit, the $\vartheta_t$ are year fixed effects, and $e_{it}$ is a random error. By using the spatial weights matrix we can allow for spatial lags, which are averages of these variables over the neighbouring units.

Our starting point is a very general model, which is a spatial autoregressive model with spatial autoregressive errors (SARAR). This model allows for spatially lagged dependent variables, spatially lagged independent variables and spatially lagged errors:

$$O_{it} = \lambda W O_{it} + \beta_1 D_{it} + \beta_2 W D_{it} + \mu_i + \vartheta_t + \rho W u_{it} + e_{it} \quad (1)$$

The SARAR model allows for changes in an outcome variable in a given area to have effects on contemporaneous outcomes in other areas (via the autoregressive spatial lag of the dependent variable, if $\lambda \neq 0$). It also allows changes in independent variables (such as getting connected to a HSR network) to affect not only own-area outcomes but also outcomes in neighbouring areas (if $\beta_2 \neq 0$). The $\rho W u_{it}$ term allows for spatial autocorrelation, where errors for a given area correlate ($\rho$) with a weighted average of the errors from surrounding areas. Equation (1) nests a spatial Durbin model if $\rho = 0$, a spatial auto-regressive model (*aka* spatial lag model) where only the dependent variable is spatially lagged if $\beta_2 = \rho = 0$, a spatial error model where only the errors are spatially lagged (if $\lambda = \beta_2 = 0$), and the most restrictive of all, which is an aspatial model with no spatial lags (if $\lambda = \beta_2 = \rho = 0$). The aspatial model has been the approach underpinning many previous studies of HSR impacts on the regional economy (as shown in Table 1). The encompassing nature of equation (1) allows for a general-to-specific model selection strategy which appears to be more robust than the reverse simple-to-general selection strategy, especially if they are any anomalies in the Data Generating Process (Mur and Angulo, 2009).

An important feature of spatial econometric models is that lags of either the outcome variable or of independent variables (but not of errors) mean that total effects of changes in an independent variable—e.g. whether a county gets connected to a HSR network—may be quite different to what the regression coefficient on the dummy variable for being connected shows. Thus, while $\hat{\beta}_1$ is the object of interest in the typical model without spatial lags, in the spatial models when either the spatial lags of outcomes or the spatial lags of independent variables are non-zero then $\hat{\beta}_1$ does not capture the total effect of a change in the administrative status of a county. A useful decomposition of the more complex spatial relationships that occur relies on rewriting equation (1) in matrix notation (for simplicity, subscripts are dropped and fixed effects and error terms combined in *v* because the errors do not affect this decomposition) as:

$$O = (I - \lambda W)^{-1}(D\beta_1 + WD\beta_2) + (I - \lambda W)^{-1}v \quad (2)$$

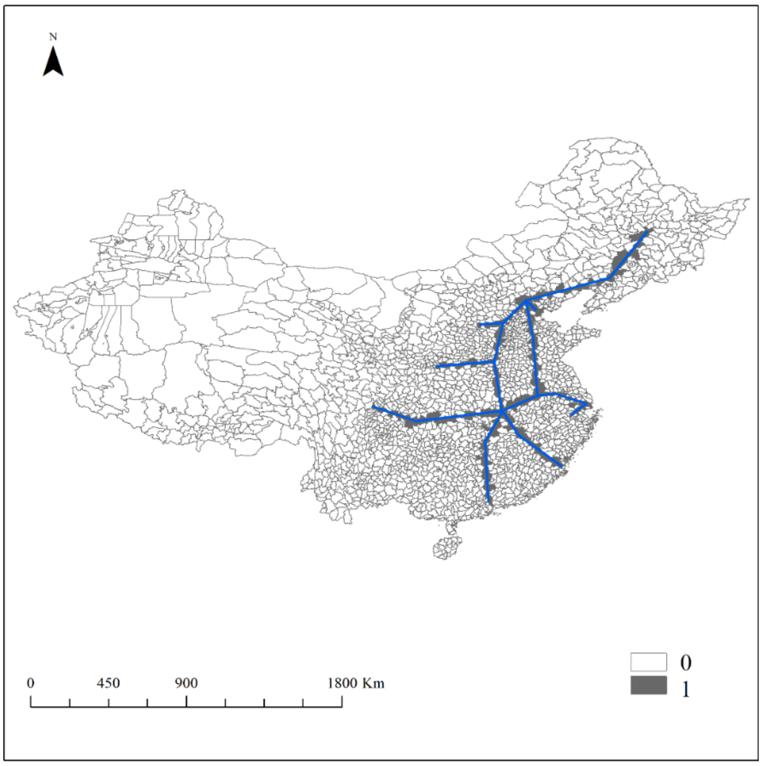
Following Elhorst (2012), the $N \times N$ matrix of partial derivatives can be written (noting that diagonal elements of $W$ are zero) as:

$$\frac{\partial O}{\partial D_k} = (I - \lambda W)^{-1}(\beta_{1k} I_N + \beta_{2k} W) \quad (3)$$

where $D_k$ is the HSR connection status in spatial unit $k$. The total marginal effect on output that is associated with a county getting connected has two components, a direct one and an indirect one, that may both vary over space. The estimator that we use follows LeSage and Pace (2009) in reporting a single direct effect, that averages the diagonal elements of the matrix in (3) and a single indirect effect that averages the row sums of the non-diagonal elements of that matrix. Indirect effects arise not just from adjacent area units, if $\beta_{2k} \neq 0$, but also from (potentially) all areas through the spatial autoregressive effect if $\lambda \neq 0$. Thus, there can be both local and global spillovers and when these are accounted for, averages from the matrix of derivatives $\partial O / \partial D_k$ may be quite different to the estimated direct impact effect, $\hat{\beta}_1$.

To further address the endogeneity of HSR route placement, we combine the IV method with equation (1). We used the straight-line strategy to construct the potential HSR connection variables, as the IV for the actual HSR connections. Compared with highways and traditional railways, early stage HSR especially aims to reduce travel time between targeted central cities. To best realize this aim, a designer might hypothetically just draw a straight line between two targeted cities. Thus, those counties and districts falling on the straight line are potential counties connected to the HSR network and this design choice can be used to construct the IV for the actual HSR connection variable. The straight-line strategy tends to produce valid IV because counties lying on the straight line of two HSR-targeted cities are more likely to have actual HSR connections, but whether or not a county is on the line is exogenous. Specifically, for each HSR line in operation, we draw a straight line between two targeted provincial capitals. Those counties on the line are potential counties for HSR connection, assigned to be in the same year the actual HSR line started to operate (see Figure 3 for an example).

Figure 3. The straight-line strategy for the instrumental variable




Note: This map illustrates the IV strategy based on potential HSR lines (shown in blue) only for 2012. The darkest areas, which take the value of 1 for the instrumental variable in the first-stage model, are the potential counties and districts connected by HSR lines based on straight lines between capital cities.

## IV. Results

*Empirical results*

The results of estimating Eq. (1) and then imposing various restrictions on the parameters and estimating the nested models are given in Table 3 (for GDP), Table 4 (for luminosity: DMSP), and Table 5 (for luminosity: VNL). The nesting restrictions are rejected in all cases, so that the SARAR models appear to be the most data-acceptable models for both GDP and luminosity. The discussion therefore concentrates mostly on the results in column (1) for the SARAR model. Nevertheless, we also devote some discussion to the results in column (5) of each table for the standard two-way fixed effects panel data model that does not allow for any spatial lags. Those sorts of aspatial models are often used in the literature (such as some of those studies summarized in Panel A and Panel C of Table 1).

Table 3: Relationships Between HSR station opening and the Change in Economic Activity (log GDP) in China: 2012 to 2019

| | (1) Spatial lag of errors, covariate and outcome | (2) Spatial lag of the covariate and outcome | (3) Spatial lag of the outcome | (4) Spatial lag of the errors | (5) Standard panel model analysis |
|---|---|---|---|---|---|
| HSR station opened | -0.005 | -0.004 | -0.007 | -0.004 | -0.025*** |
| | (0.006) | (0.006) | (0.005) | (0.006) | (0.007) |
| Average impacts: | | | | | |
| Direct | -0.004 | -0.008 | -0.008 | -0.004 | -0.025*** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) |
| Indirect | -0.005 | -0.052 | -0.016 | n.a. | n.a. |
| | (0.010) | (0.030) | (0.012) | | |
| Total | -0.009 | -0.060 | -0.024 | n.a. | n.a. |
| | (0.011) | (0.033) | (0.018) | | |
| County fixed effects | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Spatial lag: HSRopen | Yes | Yes | No | No | No |
| Spatial lag: output | Yes | Yes | Yes | No | No |
| Spatial lag: errors | Yes | No | No | Yes | No |
| All covariates = 0 | $\chi^2$=2693*** | $\chi^2$=45069*** | $\chi^2$=45071*** | $\chi^2$=2780*** | $\chi^2$=16335*** |
| Nesting restrictions | n.a. | $\chi^2$=54935*** | $\chi^2$=54953*** | $\chi^2$=2898*** | $\chi^2$=70852*** |

*Note:* The sample period is 2012-2019, for 2342 county-level units, giving an estimation sample of n=18736. Coefficients for the fixed effects and the spatial lags are not reported. The decomposition of average impacts into direct, indirect and total components is based on LeSage and Pace (2009). The nesting restrictions are imposed on the SARAR model in column (1) to derive the models in columns (2) to (5) Standard errors are in ( ), with statistical significance at the 1%, 5% and 10% level denoted by ***, **, *.

Table 4: Relationships Between HSR station opening and the Change in Luminosity (log DMSP) in China: 2012 to 2019

| | (1) Spatial lag of errors, covariate and outcome | (2) Spatial lag of the covariate and outcome | (3) Spatial lag of the outcome | (4) Spatial lag of the errors | (5) Standard panel model analysis |
|---|---|---|---|---|---|
| HSR station opened | -0.006 | -0.003 | -0.007 | -0.001 | -0.027** |
| | (0.012) | (0.012) | (0.011) | (0.012) | (0.013) |
| Average impacts: | | | | | |
| Direct | -0.001 | -0.004 | -0.007 | -0.001 | -0.027** |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.013) |
| Indirect | -0.035* | -0.105** | -0.009 | n.a. | n.a. |
| | (0.021) | (0.044) | (0.014) | | |
| Total | -0.036 | -0.108** | -0.016 | n.a. | n.a. |
| | (0.024) | (0.048) | (0.026) | | |
| County fixed effects | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Spatial lag: HSRopen | Yes | Yes | No | No | No |
| Spatial lag: output | Yes | Yes | Yes | No | No |
| Spatial lag: errors | Yes | No | No | Yes | No |
| All covariates = 0 | $\chi^2$=1667*** | $\chi^2$=21837*** | $\chi^2$=21829** | $\chi^2$=2794*** | $\chi^2$=11908*** |
| Nesting restrictions | n.a. | $\chi^2$=16119*** | $\chi^2$=16134*** | $\chi^2$=1016*** | $\chi^2$=23655*** |

*Note:* The sample period is 2012-2019, for 2342 county-level units, giving an estimation sample of n=18736. Coefficients for the fixed effects and the spatial lags are not reported. The decomposition of average impacts into direct, indirect and total components is based on LeSage and Pace (2009). The nesting restrictions are imposed on the SARAR model in column (1) to derive the models in columns (2) to (5) Standard errors are in ( ), with statistical significance at the 1%, 5% and 10% level denoted by ***, **, *.

Table 5: Relationships Between HSR station opening and the Change in Luminosity (log VNL) in China: 2012 to 2019

| | (1)<br>Spatial lag of errors, covariate and outcome | (2)<br>Spatial lag of the covariate and outcome | (3)<br>Spatial lag of the outcome | (4)<br>Spatial lag of the errors | (5)<br>Standard panel model analysis |
|---|---|---|---|---|---|
| HSR station opened | -0.049*** | -0.043*** | -0.044*** | -0.044*** | -0.056*** |
| | (0.010) | (0.009) | (0.009) | (0.009) | (0.010) |
| Average impacts: | | | | | |
| Direct | -0.046*** | -0.047*** | -0.048*** | -0.044*** | -0.056*** |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.010) |
| Indirect | -0.019 | -0.063* | -0.053*** | n.a. | n.a. |
| | (0.016) | (0.034) | (0.011) | | |
| Total | -0.065*** | -0.110** | -0.101*** | n.a. | n.a. |
| | (0.019) | (0.037) | (0.020) | | |
| County fixed effects | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Spatial lag: HSRopen | Yes | Yes | No | No | No |
| Spatial lag: output | Yes | Yes | Yes | No | No |
| Spatial lag: errors | Yes | No | No | Yes | No |
| All covariates = 0 | $\chi^2$=1822*** | $\chi^2$=21950*** | $\chi^2$=21950*** | $\chi^2$=2180*** | $\chi^2$=12775*** |
| Nesting restrictions | n.a. | $\chi^2$=15956*** | $\chi^2$=15957*** | $\chi^2$=1090*** | $\chi^2$=22394*** |

*Note:* The sample period is 2012-2019, for 2342 county-level units, giving an estimation sample of n=18736. Coefficients for the fixed effects and the spatial lags are not reported. The decomposition of average impacts into direct, indirect and total components is based on LeSage and Pace (2009). The nesting restrictions are imposed on the SARAR model in column (1) to derive the models in columns (2) to (5) Standard errors are in ( ), with statistical significance at the 1%, 5% and 10% level denoted by ***, **, *.

The lack of data acceptability for any of the nesting restrictions indicates that for the spatial units and period we study, the interactions are occurring through the spatial lags of the outcomes, the lags of the treatment, and the lags of the errors. There are two consequences of this pattern. First, partial approaches that only allow for local spillovers, such as including the treatment status of nearby spatial units, may not reveal the full pattern of spillovers. Second, the regression coefficients by themselves do not tell the full story, and the matrices of marginal effects based on equation (3) need to be taken into consideration.

The results of the marginal effects calculations are reported in the "average impacts" rows of Tables 3, 4, and 5, using the decomposition due to LeSage and Pace (2009). These results do not indicate that HSR expansion had a positive effect on the regional economy. From column (1) of Table 3 we cannot rule out that the HSR connection has zero direct, indirect and total effect on local GDP. For the aspatial model that does not consider the spatial spillovers, column (5) of Table 3, suggests that the HSR connection is associated with post-connection local GDP being -2.5% lower compared to what it would have been based on the GDP growth of the counties without connections. The inhibiting effect on local GDP growth of a county being connected with HSR is seen very clearly with the aspatial model.

The lack of any apparent effect of HSR connections on local GDP growth should not be due to insufficient variation in the data or a research design that is somehow 'under-powered'. The same annual GDP data, for the same spatial units, and with the same set of estimators as in Table 3, has recently been used by Zhang et al (2024) to study direct and indirect impacts on economic activity from China's counties being administratively upgraded. In the table in that study that corresponds to Table 3 here, nine of the 11 average impact estimates were sufficiently precisely estimated to be statistically significant at $p<0.01$ and another was significant at the $p<0.05$ level. So it seems to be something more about the lack of impact of HSR connections, rather than issues with the data and estimation framework, that accounts for the imprecise estimates.

When luminosity is used as the proxy for local activity, as a sensitivity analysis in case of mistrust in China's GDP figures, connection to the HSR network is associated with lower rates of growth in local economic activity. Using DMSP data, for the standard two-way fixed effects panel model without considering any spatial spillovers, the results in column (5) of Table 4 suggest an impact of almost minus three percent ($p<0.05$). This effect is even larger with the spatial Durbin model (in column (2)); luminosity is 11 percent lower after connection to the HSR network compared to the luminosity growth exhibited by the counties that remain unconnected. This negative effect operates almost entirely through the indirect impacts, suggesting that there are negative spillovers from the expansion of the HSR network. The predominance of the indirect negative impacts also shows up with the SARAR results in column (1) of Table 4, but each type of impact is surrounded by wide standard errors so that indirect and total effects would only be statistically significant at $p<0.09$ and $p<0.13$.

The clearest evidence on the negative impacts of HSR connection is with the VNL data, which are known to be far more precise and accurate than DMSP data.[1] The impact is almost minus six percent with the standard two-way fixed effects panel model without considering any spatial spillovers (Table 5, column (5)). In fact, across all five estimators in Table 5, the estimates of average direct impacts tightly group, varying only between -4.4% and -5.6%. Variation in estimates of total impacts comes from the indirect effects that range from a statistically insignificant -2% for the SARAR model to weakly significant -6.3% for the spatial Durbin model and a very precisely estimated -5.3% with the spatial lag model. Overall, no result in Table 5 gives support to a hypothesis of greater local economic activity after connection to the HSR network, but there is consistently strong evidence of negative effects from the expansion of HSR connections between 2012 and 2019.

*Results from instrumental variables*

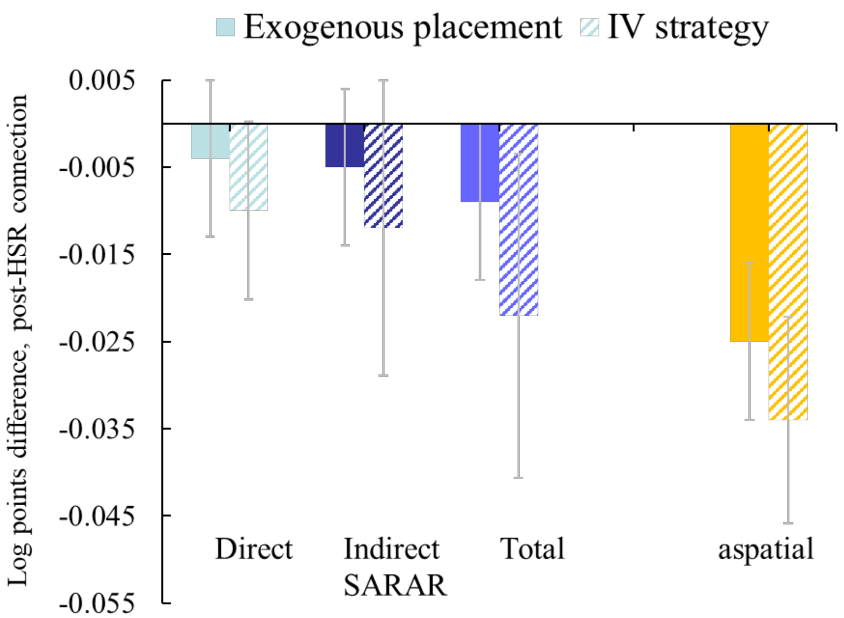
The results reported thus far are potentially biased, if the issue of endogenous placement of the HSR network matters. We therefore used an instrumental variables approach based on straight-lines which connect the major provincial cities, similar to An et al. (2022) and Liu et al. (2022). In the first stage of the two-stage least square (2SLS) results we examined the strength of this instrumental variable, with a value of the F-statistic of 1038 for omitting it from the first stage equation. Therefore, we should not have any weak instruments problem. We then repeated the models from columns (1) and (5) of Tables 3 and 5, for GDP and VNL luminosity, but using the predicted HSR connections as instruments for actual connections. The results are shown in Figure 4, with the GDP results in the top panel and the VNL results in the bottom panel.

[1] Prior study for China shows that county-level inequality measured with VNL data is far closer to benchmark estimates than what DMSP data show (Zhang et al, 2023) and a similar result is shown at the district-level in India (Mathen et al, 2024). In terms of evaluating treatment effects of spatially targeted interventions, Kim et al (2024) show that VNL data provide far more precise treatment effect estimates than do DMSP data.

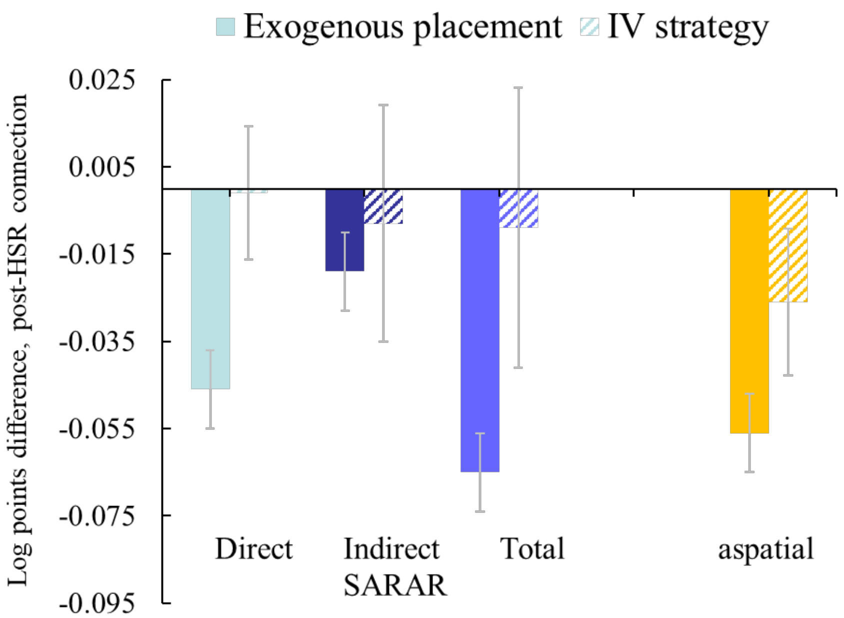
The finding of negative average total impacts on local GDP from connecting to the HSR network is amplified when the instrumental variables method is used to deal with the endogenous placement issue. The estimate of the average total impacts is more than doubled (thus, more negative) and even allowing for the larger standard errors with instrumental variables, this is a statistically significant ($p<0.05$) finding. Likewise, with aspatial two-way fixed effects, which already yielded a precisely estimated impact of -2.5% ($p<0.01$) when assuming exogenous placement, the effect when using instrumental variables becomes even more negative, at -3.4% (Fig 4a). Conversely, when luminosity (log VNL) is used to indicate local economic activity the use of instrumental variables causes the estimated impacts to become smaller (thus, less negative). This attenuation of the estimated negative impacts occurs with both the SARAR model and also the aspatial model. With the IV results for luminosity, one could not rule out a hypothesis of there being no effect on local economic activity from connecting to the HSR network (Fig. 4b).

**Figure 4.** Comparing HSR impacts with exogenous versus endogenous placement

**(a) log GDP as outcome variable**




**(b) log VNL luminosity as outcome variable**




Notes: Error bars show 95% CI. The IV strategy uses hypothetical straight-line connections between city pairs. Exogenous placement results are from Tables 3 and 5, column (1) and (5)

## V. Discussion and Conclusions

A dramatic expansion of high-speed rail in China presents an important empirical setting to study the impact of transport infrastructure enhancement on economic growth. Given this importance, a growing literature with dozens of studies has examined high-speed rail impacts in China. What we add to this literature is a consideration of both spatial spillovers and the endogenous placement of the high-speed rail network. Most prior studies ignore any spatial spillovers, as shown in our review of 30 papers. Indeed, we are aware of only two studies that consider both the endogeneity and the spillover issue. The other feature of our study is that we cover all parts of China, using panel data for 2342 county-level units. Many of the prior studies have focused only on a particular region, or have used more spatially aggregated data for prefectural-level cities. The growing national scope of China's high-speed rail network, and the ambition to almost double the network length over the next decade, makes a national scope for the analysis more salient.

In the period under study, the number of county-level units in China that are connected to the high-speed rail network more than tripled, with almost one-fifth of all county-level units now connected to the network. Despite this substantial increase in connectivity, our results do not show positive impacts on local economic activity. Instead, we predominantly find negative impacts, or cannot rule out nil impacts, whether allowing for spatial spillovers or not, whether allowing for endogeneity or not, and using both GDP and luminosity data as our measures of local economic activity. In this regard, our findings echo Qin (2017) and Gao et al. (2020), who note that connecting to the high-speed rail network can impede economic growth through the spatial reallocation of the economically active population from peripheral areas to more central areas, and through the spatial restructuring of industries.

Of course the priority given to investments in high-speed rail may not just be because of expected positive impacts on local GDP. The Chinese government proactively promotes indigenous technology innovation, with the high-speed rail industry a prominent example of innovation-driven development (Sun, 2015). By developing high-speed rail technology, the Chinese state successfully leapfrogged into the high-speed land transportation age, fostering innovation, and reducing dependency on foreign suppliers (Yan, 2023). These technologies serve as a fruitful starting point for China in promoting infrastructure construction in a globalized economy, such as through the Belt and Road Initiative. Moreover, even if it does not (yet) show up in local GDP, the growth of high-speed rail may improve corporate financing efficiency and optimise the efficiency of resource allocation in capital markets (Jin, Zhang, and Xin, 2020). For example, being connected to the network significantly increases a city's capital mobility (Duan et al. 2021), and the resource redistribution between regions (Meng, Lin, and Zhu 2018).

Notwithstanding these considerations, the apparent negative impacts on county-level economic growth, and potentially negative spillover effects on neighbouring spatial units does pose a problem as China adapts to lower expectations of future economic growth. Before planning and constructing future additions to the high-speed rail network, and future stations on the network, policy makers may need to do more thorough evaluation of economic impacts on the targeted county-level units and also on their neighbours.

Future research could delve into the heterogeneous effects of high-speed rail on economic growth and explore broader impacts on the environment and on society. For example, some studies have proposed that impacts of high-speed rail spatially vary along the route, tending to benefit developed cities with several rail stations and higher accessibility rather than least-developed and developing cities with remote locations and backward economies (Liang et al., 2020; Zou and Chen, 2024). Furthermore, any spillover effects may be examined using a broader set of weighting matrices to what we have used, such as allowing for asymmetric effects that reflect greater agglomeration forces in some directions rather than others, or in some regions rather than others (as discussed, for example, in Zhang et al, 2024). These potential refinements provide a direction and focus for our future research.

## References


Ahlfeldt, G. M., and Feddersen, A. (2018). From periphery to core: measuring agglomeration effects using high-speed rail. *Journal of Economic Geography*, 18(2), 355-390.

Albalate, D., Campos, J., and Jiménez, J. L. (2023). Local tourism effects of HSR in small cities: three synthetic control case studies. *Current Issues in Tourism*, 26(14), 2301-2316.

An, Y., Wei, Y. D., Yuan, F., and Chen, W. (2022). Impacts of high-speed rails on urban networks and regional development: A study of the Yangtze River Delta, China. *International Journal of Sustainable Transportation*, 16(6), 483-495.

Banerjee, A., Duflo, E., and Qian, N. (2020). On the road: Access to transportation infrastructure and economic growth in China. *Journal of Development Economics*, 145, 102442.

Carbo, J. M., Graham, D. J., Anupriya, Casas, D., and Melo, P. C. (2019). Evaluating the causal economic impacts of transport investments: evidence from the Madrid–Barcelona high speed rail corridor. *Journal of Applied Statistics*, 46(9), 1714-1723.

Cascetta, E., Cartenì, A., Henke, I., and Pagliara, F. (2020). Economic growth, transport accessibility and regional equity impacts of high-speed railways in Italy: Ten years ex post evaluation and future perspectives. *Transportation Research Part A: Policy and Practice*, 139, 412-428.

Chen, Z. (2019). Measuring the regional economic impacts of high-speed rail using a dynamic SCGE model: the case of China. *European Planning Studies*, 27(3), 483-512.

Chen, H., Cheng, K., and Zhang, M. (2023). Does geographic proximity affect firms' cross-regional development? Evidence from high-speed rail construction in China. *Economic Modelling*, 106402.

Chen, M., Liu, X., Xiong, X., and Wu, J. (2023). Has the opening of high-speed rail narrowed the inter-county economic gap? The perspective of China's state-designated poor counties. *International Review of Economics and Finance*.

Chen, Y., Lv, Y., and Zhang, Y. (2024). The impact of high-speed railway construction on regional economic development in Hubei Province. *Management System Engineering*, 3(1), 3.

Chen, Q., and Wang, M. (2022). Opening of high-speed rail and the consumer service industry: Evidence from China. *Economic Analysis and Policy*, 76, 31-45.

Chong, Z., Chen, Z., and Qin, C. (2019). Estimating the economic benefits of high-speed rail in China. *Journal of Transport and Land Use*, 12(1), 287-302.

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.

Dong, L., Du, R., Kahn, M., Ratti, C., and Zheng, S. (2021). "Ghost cities" versus boom towns: Do China's high-speed rail new towns thrive? *Regional Science and Urban Economics*, 89, 103682.

Duan, L., Niu, D., Sun, W., and Zheng, S. (2021). Transportation infrastructure and capital mobility: Evidence from China's high-speed railways. *The Annals of Regional Science*, 67, 617-648.

Egger, P. H., Loumeau, G., and Loumeau, N. (2023). China's dazzling transport infrastructure growth: Measurement and effects. *Journal of International Economics*, 142, 103734.

Elvidge, C. D., Zhizhin, M., Ghosh, T., Hsu, F.-C., and Taneja, J. (2021). Annual time series of global VIIRS nighttime lights derived from monthly averages: 2012 to 2019. *Remote Sensing*, 13(5), 922.

Facchinetti-Mannone, V. (2019) A methodological approach to analyze the territorial appropriation of high-speed rail from interactions between actions and representations of local actors, *European Planning Studies*, 27(3), pp. 461–482.

Gao, Y., Song, S., Sun, J., and Zang, L. (2020). Does high-speed rail connection really promote local economy? Evidence from China's Yangtze River Delta. *Review of Development Economics*, 24(1), 316-338.

Guan, C., Chen, L., and Li, D. (2023). Does the opening of high-speed railway improve high-quality economic development in the Yangtze River Delta, China? *Land*, 12(8), 1629.

Guo, H., Chen, C., Dong, X., and Jiang, C. (2021). The evolution of transport networks and the regional water environment: the case of Chinese high-speed rail. *Regional Studies*, 55(6), 1084-1110.

Guo, Y., Yu, W., Chen, Z., and Zou, R. (2020). Impact of high-speed rail on urban economic development: An observation from the Beijing-Guangzhou line based on night-time light images. *Socio-Economic Planning Sciences*, 72, 100905.

Huang, Y. (2021). Spatial and temporal heterogeneity of the impact of high-speed railway on urban economy: Empirical study of Chinese cities. *Journal of Transport Geography*, 91, 102972.

Jin, M., Gu, R., Li, K. X., Shi, W., and Xiao, Y. (2024). Heterogeneous impacts of the high-speed railway network on urban–rural income disparity: Spatiotemporal evidence from Yangtze River Delta of China. *Transportation Research Part A: Policy and Practice*, 183, 104050.

Jin, Z., Zhang, L., and Xin, Q. (2020). Transportation infrastructure and resource allocation of capital market: Evidence from high-speed rail opening and company going public. *China Journal of Accounting Studies*, 8(2), 272-297.

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.

Kim, E., and Yi, Y. (2019). Impact analysis of high-speed rail investment on regional economic inequality: a hybrid approach using a transportation network-CGE model. *Journal of Transport Economics and Policy*, 53(3), 314-333.

Kim, B., Gibson, J., & Boe-Gibson, G. (2024). Measurement errors in popular night lights data may bias estimated impacts of economic sanctions: Evidence from closing the Kaesong Industrial Zone. *Economic Inquiry*, 62(1), 375-389.

Kuang, C., Liu, Z., and Zhu, W. (2021). Need for speed: High-speed rail and firm performance. *Journal of Corporate Finance*, 66, 101830.

LeSage, J., and Pace, R. K. (2009). Introduction to spatial econometrics. Chapman and Hall/CRC.

Li, H., Dong, X., Jiang, Q., and Dong, K. (2021). Policy analysis for high-speed rail in China: Evolution, evaluation, and expectation. *Transport Policy*, 106, 37-53.

Li, M., and Li, H. (2024). Impacts of high-speed rail on regional economic growth: an empirical analysis of the moderated mediation effects. *Transportation Research Record*, 2678(3), 476-492.

Li, X., Wu, Z., and Zhao, X. (2020). Economic effect and its disparity of high speed rail in China: A study of mechanism based on synthesis control method. *Transport Policy*, 99, 262-274.

Li, J., Yu, Q., and Ma, D. (2024). Does China's high-speed rail network promote inter-city technology transfer? ——A multilevel network analysis based on the electronic information industry. *Transport Policy*, 145, 11-24.

Liang, Y., Zhou, K., Li, X., Zhou, Z., Sun, W., and Zeng, J. (2020). Effectiveness of high-speed railway on regional economic growth for less developed areas. *Journal of Transport Geography*, 82, 102621.

Liu, Z., Diao, Z., and Lu, Y. (2024). Can the opening of high-speed rail boost the reduction of air pollution and carbon emissions? Quasi-experimental evidence from China. *Socio-Economic Planning Sciences*, 92, 101799.

Liu, X., Li, H., Sun, Y., and Wang, C. A. (2022). High-speed railway and urban productivity disparities. *Growth and Change*, 53(2), 680-701.

Liu, Y., Tang, D., and Wang, F. (2024). Research on the spatial spillover effect of high-speed railway on the income of urban residents in China. *Humanities and Social Sciences Communications*, 11(1), 1-13.

Luan, Z., Guo, S., and Liang, W. (2024). Can the construction of a high-speed rail alleviate haze pollution: an empirical analysis based on social networks and dynamic spatial econometric models. *Environmental Science and Pollution Research*, 1-17.

Ma, G. R., Chen, X. M., and Yang, E. Y. (2020). How transportation infrastructure promotes capital flow: A study based on the opening of high-speed rail and the off-site investment of listed companies. *China Industrial Economics*, 2020(06), 5-23.

Mathen, C., Chattopadhyay, S., Sahu, S., & Mukherjee, A. (2023). Which nighttime lights data better represent India's economic activities and regional inequality? *Asian Development Review,* 41(2), (online ready)

Mei, L., and Zhang, N. (2021). Catch up of complex products and systems: lessons from China's high-speed rail sectoral system. *Industrial and Corporate Change*, 30(4), 1108-1130.

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.

Miwa, N., Bhatt, A., and Kato, H. (2022). High-speed rail development and regional inequalities: Evidence from Japan. *Transportation Research Record*, 2676(7), 363-378.

Mur, J., and Angulo, A. (2009). Model selection strategies in a spatial setting: Some additional results. *Regional Science and Urban Economics*, 39(2), 200-213.

Qin, Y. (2017). 'No county left behind?' The distributional impact of high-speed rail upgrades in China. *Journal of Economic Geography*, 17(3), 489-520.

Qiu, Z., Liu, D., and Liao, Q. (2023). Can the opening of China railway express reduce urban carbon emissions? A difference-in-differences analysis in China. *Frontiers in Environmental Science*, 10, 2686.

Ren, J. J., Liu, W. G., Lai, J. L., Ye, W. L., Deng, S. J., Liu, X. Y., and Tan, B. (2024). Performance deterioration and structural state diagnosis of slab tracks for high-speed railways: A review. *Engineering Failure Analysis*, 107955.

Shen, S., Li, H., and Li, M. (2023). Transportation infrastructure and digital economy—Evidence from Chinese Cities. *Sustainability*, 15(22), 16024.

Shi, K., and Wang, J. (2024). The influence and spatial effects of high-speed railway construction on urban industrial upgrading: Based on an industrial transfer perspective. *SocioEconomic Planning Sciences*, 93, 101886.

Sun, Z. (2015). Technology innovation and entrepreneurial state: the development of China's high-speed rail industry. *Technology Analysis and Strategic Management*, 27(6), 646-659.

Sun, X., Yan, S., Liu, T., and Wang, J. (2023). The impact of high-speed rail on urban economy: Synergy with urban agglomeration policy. *Transport Policy*, 130, 141-154.

Tang, H., Zhang, J., Fan, F., and Wang, Z. (2024). High-speed rail, urban form, and regional innovation: A time-varying difference-in-differences approach. *Technology Analysis and Strategic Management*, 36(2), 195-209.

Tian, M., Li, T., Ye, X., Zhao, H., and Meng, X. (2021). The impact of high-speed rail on service industry agglomeration in peripheral cities. *Transportation Research Part D*, 93, 102745.

Wang, C., Chen, J., Li, B., Chen, N., and Wang, W. (2023). Impact of high-speed railway construction on spatial patterns of regional economic development along the route: A case study of the Shanghai–Kunming high-speed railway. *Socio-Economic Planning Sciences*, 87, 101583.

Wang, K. L., Jiang, W., and Miao, Z. (2023). Impact of high-speed railway on urban resilience in China: Does urban innovation matter? *Socio-Economic Planning Sciences*, 87, 101607.

Wang, F., Liu, Z., Xue, P., and Dang, A. (2022). High-speed railway development and its impact on urban economy and population: A case study of nine provinces along the yellow river, China. *Sustainable Cities and Society*, 87, 104172.

Wang, J., Wang, L., Zhang, Y., Zhang, J., Li, J., and Li, S. (2024). A georeferenced dataset for mapping and assessing subgrade defects in China's high-speed railways. *Scientific Data*, 11(1), 293.

Wang, C. A., Wu, J., and Liu, X. (2022). High-speed rail and urban innovation: based on the perspective of labor mobility. *Journal of the Asia Pacific Economy*, 1-26.

Wang, B., Yu, F., and Zhang, M. (2023). The heterogeneous economic impacts of distance to high-speed railway stations in China. *International Journal of Business and Management*, 16(2), 1-75.

Wang, S., Zhou, Y., Guo, J., and Mao, J. (2023). Did high speed rail accelerate the development of tourism economy?–Empirical analysis from Northeast China. *Transport Policy*, 143, 25-35.

Xu, W., and Huang, Y. (2019). The correlation between HSR construction and economic development-empirical study of Chinese cities. *Transportation Research Part A: Policy and Practice*, 126, 24–36.

Yan, K. (2023). Market-creating states: rethinking China's high-speed rail development. *Review of International Political Economy*, 30(4), 1220-1237.

Yang, Y., and Ma, G. (2023). How can HSR promote inter-city collaborative innovation across regional borders? *Cities*, 138, 104367.

Yang, Q., Wang, Y., Liu, Y., Liu, J., Hu, X., Ma, J., and Tao, S. (2023). The impact of China's high-speed rail investment on regional economy and air pollution emissions. *Journal of Environmental Sciences*, 131, 26-36.

Yao, S., Zhang, F., Wang, F., and Ou, J. (2019). Regional economic growth and the role of high-speed rail in China. *Applied Economics*, 51(32), 3465-3479.

Yu, L. (2021). Study on treatment effects and spatial spillover effects of Beijing–Shanghai HSR on the cities along the line. *The Annals of Regional Science*, 67(3), 671-695.

Yu, J., Zhou, Y., Huang, Q., Li, X., Hou, Y., and Wang, X. (2021). Analysis of the impact of high-speed railway on county economic development based on the synthetic control method: The Hubei province in China. *Mathematical Problems in Engineering*, 2021, 1-16.

Zhang, X., and Gibson, J. (2022). Using multi-source nighttime lights data to proxy for county-level economic activity in China from 2012 to 2019. *Remote Sensing*, 14(5), 1282.

Zhang, X., Gibson, J., & Deng, X. (2023). Remotely too equal: Popular DMSP night-time lights data understate spatial inequality. *Regional Science Policy & Practice*, 15(9), 2106-2125.

Zhang, X., Li, C., and Gibson, J. (2024). The role of spillovers when evaluating regional development interventions: evidence from administrative upgrading in China. *Letters in Spatial and Resource Sciences*, 17(1), 9.

Zou, W., and Chen, L. (2024). The impact of high-speed railway on firms' productivity. *International Review of Economics and Finance.*