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The varying effects of accessing high-speed rail system on China's county development: A geographically weighted panel regression analysis

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ABSTRACT

The construction of high-speed rail in China was initiated to answer increasing demand for fast and convenient transportation systems connecting large economic centers. After the first high-speed rail was open for operation and the initial adjustment period, access to high-speed rail starts to bring fundamental changes in regional economic operation modes in China and drastically increase interconnectivity among places that are used to be farther apart. It is commonly understood that access to HSR will have significant impact on economic development. It is, however, also quite possible that the benefits to economic development brought by HSR will have a diminishing marginal effect. That is to say, the benefits brought by HSR to economic development tend to be the greatest when access to HSR is scarce. The benefits will decrease once access to HSR becomes more frequent. With data of HSR stations distribution and a set of panel data of socioeconomic information at county-level from 2008 – 2015 in China, this study creates four HSR accessibility indices and attempts to provide insights on how access to the HSR system supports China's county-level development. The first one simply measures the geographic distributions of HSR stations and feed the data to a global spatial panel model to investigate whether the presence of an HSR station will have significant impact on county development. The second one directly measures the accessibility to HSR based on road network travel time. The third one measures a Euclidean distance from the geometric center of the county to the nearest HSR station. The fourth one is an inclusive and inversed distance measure attempting to capture HSR's geographic influence. The last three indices will be used in a geographically weighted panel regression model to test the potential varying relationships between HSR accessibility and county development, controlling other socioeconomic factors. Our results suggest that on average the presence of an HSR station suggests about 2.7 % increase of that county's per capita GDP. The geographically weighted panel regression suggests that in places where HSR is sparsely distributed (access to HSR is scarce and less frequent), the relationship between HSR accessibility and GDP per capita is significant and positive. In places where HSR is densely distributed (access to HSR is more frequent), the relationship is less apparent. The current study explores the distribution of HSR and its contribution to county development in China. We hope the results will offer significant insights of the relationships between infrastructure construction and county economic development in both China and beyond.

1. Introduction

The construction of high-speed rail (HSR) in China was a direct response to the increasing demands of fast and convenient transportation systems between large economic centers (Yang et al., 2018). The inauguration of the first HSR line in China forever changed the accessibility landscape between Chinese places (urban and rural areas alike). Although the primary function of HSR is for passenger transportation, as one of the most important production factors, the increased human (labor force) mobility and shortened actual cost of movement (measured by time) also brought fundamental changes to the economic landscape in China (Chen and Vickerman, 2017; Kim et al., 2018; Meng et al., 2018; Xu et al., 2018). Studies employ a variety of approaches to investigate how HSR and China's economic landscape is related at

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various spatial scales are quite abundant. For instance, Zhou and Li (2018) apply a difference-in-difference method and a set of panel data at the city (prefecture) level to study the HSR accessibility's impact on China's tourism economies. Meng et al. (2018) employ the propensity score-matching difference-in-difference method and a set of county-level panel data from 2006 to 2014 to understand how the establishment of an HSR station will impact county development. Xu et al. (2018) generate a comprehensive connectivity-accessibility index for China's HSR network and evaluate how HSR construction impact cities. Ke et al. (2017) evaluate HSR's effect on prefecture-level city's economic growth with a panel data program evaluation method (Hsiao et al., 2012). Their results resonate with the transformative effect of HSR as proposed in Vickerman (2018), which suggests places that are better prepared for HSR often gain more from HSR construction and deployment than places that are less well prepared.

With increasing amount of data and fast developing analytical methodologies, our understanding of HSR construction / HSR station deployment and how they impact the local economic landscape is increasing drastically. This is especially true when scholars started to apply spatial analytical approaches to understand the issue since HSR construction and deployment and how it relates to local economic development is essentially a geographical problem (Chen and Haynes, 2015b; Dou et al., 2016; Ortega et al., 2018). Still, application of more in-depth spatial data analysis-oriented approaches to understand the relationship between HSR construction and deployment and local economic development merits further investigation.

Many scholars argue that the impact of HSR is not likely universal on local economic development (Chen and Haynes, 2017; Hiramatsu, 2018; Jin et al., 2017; Wang et al., 2016b). As eloquently argued in Vickerman (2018); Chen and Vickerman (2017); Jin et al. (2017), among others, the benefits of HSR construction and deployment to local economic development are more likely varying with location. The “transformative effect” or “wider economic impact” of HSR only manifests in places that have sufficient infrastructure and economic foundations.

Still, HSR construction and deployment in China are not entirely an economy-driven event. Places do have to compete for the deployment of HSR stations to their favor. The decision, however, is not entirely based on economic performance or infrastructure preparedness. Instead, construction of HSR in China also carries significant political economic agenda (Garmendia et al., 2012; Wang et al., 2013). Many Chinese HSR stations are often located farther away from the centers of cities for the purpose of stimulating the peripheral areas' economic development. Considering the vast territory of China and the fact that close to half of its gigantic population still lives in rural areas, the strategy is one such tactic the Central Government employs to stimulate rural development (He et al., 2016; Liu et al., 2013; Lo et al., 2016). The strategy suggests that the relationship between HSR accessibility and local economic development might not follow strictly the economy-driven model. The relationship will likely vary based on locations but to predict such varying relationship requires fundamentally different approach that deals with spatially varying relationships directly.

Methodological development in recent decade has seen great progress in the field of spatially varying coefficient models. Common methods include the geographically weighted regression (GWR) (Fotheringham et al., 2002), Bayesian spatially varying coefficient model (Congdon, 2003; Gelfand et al., 2003) and eigenfunction based spatial filtering approaches (Griffith, 2008; Helbich and Griffith, 2016; Murakami and Griffith, 2019). These methods, however, are mainly applied to cross-sectional data. Application of spatially varying coefficient models to panel data remains limited, though in Gelfand et al. (2003), the Bayesian spatially varying coefficient model can be extended to Bayesian spatially and temporally varying coefficient model. Lack of easily executable software packages or platform that such model can be easily implemented prevents wide application of the useful method. On the other hand, Yu (2010); Cai et al. (2014) and Yu (2014) explored the potentials of applying the geographically weighted regression approach to panel data. Their analytical results suggest that as an exploratory approach, the geographically weighted panel regression (GWPR) produces potentially more realistic results than annual cross-sectional GWR analyses or the global spatial econometric panel regression models.

The current study extends on Yu (2010) and Yu (2014)'s proposal of the GWPR and develops an analytical framework that might produce a viable spatially varying coefficient model with panel data. Using the GWPR approach, this study attempts to evaluate the spatially varying relationship between access to HSR and county's economic development with a set of panel data from 2008 to 2015 in China.

Following this introduction section, we will discuss briefly the HSR development in China and how it might be related with local, especially county economic development. This is followed by the discussion of crafting four HSR accessibility measuring indices from different perspectives. The other data that will be used in the study is also introduced there. The fourth section presents the development of a geographically weighted panel regression framework, the rationale, bandwidth selection method, and estimation approaches. We present the analytical results in section five and discuss these findings in detail in regard to how a county's accessibility to the HSR system impacts its own economic development, and how such impacts might vary from place to place. We conclude our study in section six with a summary and future research foci.

2. High speed rail development in China

Although it was contemplated in the late 1990s and early 2000s, the actual construction of the first high speed rail line in China (the intercity Beijing-Tianjin High Speed Rail) was not in operation until 2008. The effect of shortened travel time was immediate and multifaceted. Though designed as a passenger transportation means, the increased mobility of people among the large economic centers changed not just how people travel, but also the overall economic landscape, investment destinations, market integration, industrial structure and rural development (Albalate et al., 2017; Campa et al., 2016; Carteni et al., 2017; Chan and Yuan, 2017; Chen and Haynes, 2015a; Gutierrez et al., 2018; Hiramatsu, 2018; Masson and Petiot, 2009; Wang et al., 2018a, b; Wang et al., 2017, 2014; Wang et al., 2016a). Construction of high speed rail is one of the primary infrastructure investments in the past decade that facilitates the development and integration of urban agglomerations (Fang and Yu, 2016, 2017; Fang et al., 2018) and promotes the New Countryside Construction in China (Liu et al., 2013). The fast (average travel speed ranging from 250 km/h to 350 km/h, more than double the regular train's speed), convenient and almost always on-time operation of the HSR in China created a new social and economic geographical landscape in China. The construction of HSR, as suggested in the New Economic Geography theory (Fujita and Krugman, 2004; Krugman, 1991; Vickerman, 2018), brings better accessibility and more integration potentials for places. This is because of both the speed and convenience of the HSR system and the increased transportation infrastructure investment and other public service sectors in places where HSR is deployed. The benefits of HSR deployment hence go beyond pure accessibility convenience. It also serves as a local economic development incentive to boost development in relatively underdeveloped regions (Yu et al., 2020). The cost is undoubtfully enormous. The immediate return is likely no match to the initial investment. Encouraging the development of underdeveloped regions through HSR construction, however, might provide a long-term social and economic benefit that might not be directly measurable by monetary terms. In other words, the externality of the HSR in the less developed regions might promote balanced regional development to trade off the cost of the construction and maintenance of the HSR lines in relatively remote areas. Such rationale is apparently what the Chinese government took in the past decade when expanding its enormous HSR network. By the end of 2018,

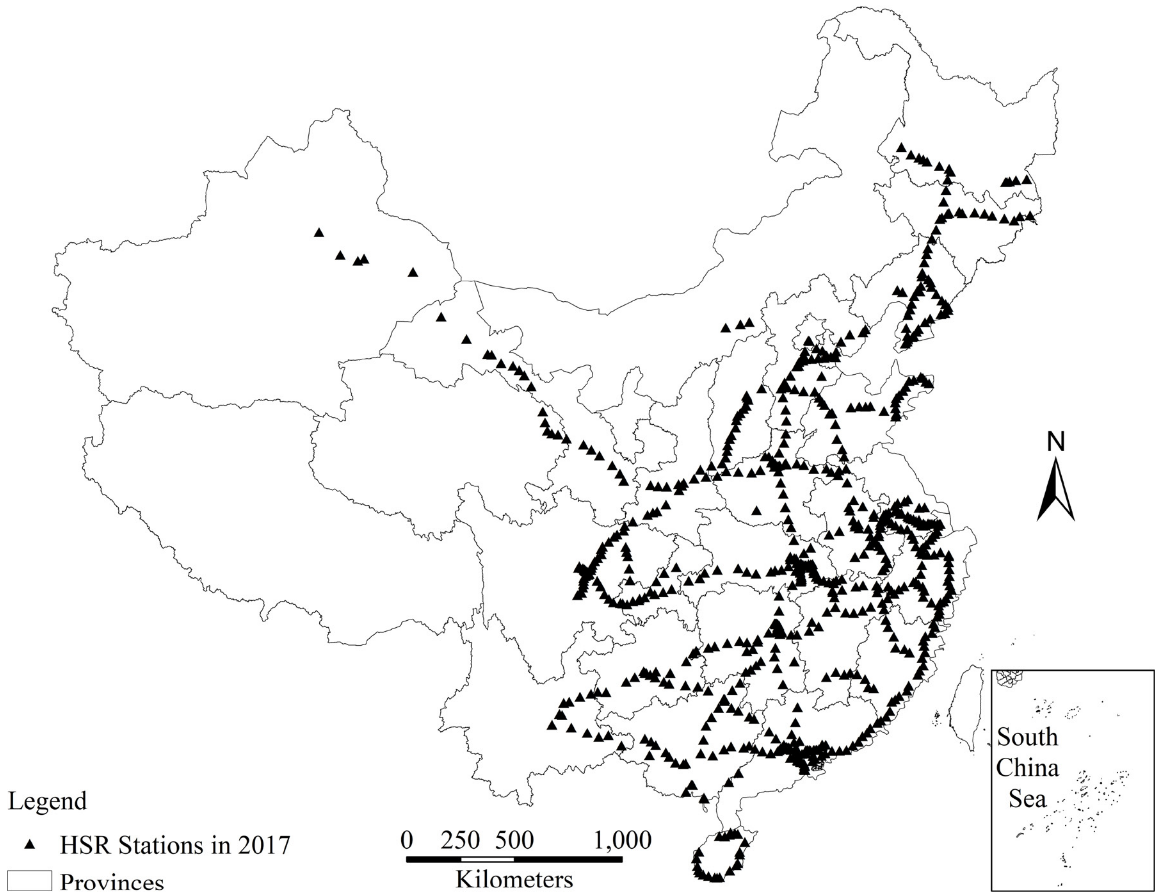

Fig. 1. Spatial distribution of high-speed rail stations in China in 2017.

the total length of China's HSR lines reached 29,000 km, more than 2/3 of all the HSR lines in the entire world. It is expected that another 3200 km new lines will be built in 2019, which enables China's total HSR lines to reach over 30,000 km in 2020. There were 728 HSR stations by the end of 2017 (when our latest HSR data is collected). These stations cover every mainland provincial administrative units except for Tibet and Ningxia. Fig. 1 shows the spatial distribution of all the HSR stations by the end of 2017. The policy signal is clear. People is the most important production factor, as the late Chinese leader, Mr. Deng Xiaoping once commented. Construction of HSR carries the high hope that help (for economic development) can come to places more efficiently when needs arise. This is the single most important infrastructure investment support and land use policy implementation for the enormous task of New Countryside Construction. The task aims at developing the underdeveloped rural areas in China, and promoting the Greater West Development that seeks to balance regional development among China's three regions (Liu, 2018; Liu et al., 2014, 2018; Yu and Wei, 2003). The potential overall benefits and the ideology that socialist economy emphasizes on regional equal development are worth the enormous initial investment and continuous maintenance of the facility.

Though scholars have engaged in exploring whether such benefits indeed manifest in China in recent years (Chen and Haynes, 2017; Jiao et al., 2014; Jin et al., 2017; Ke et al., 2017), more in-depth studies with various methodologies might provide more evidence to the hypothesis (Yu et al., 2020). If left to its own development and self-organization, as suggested in Vickerman (2018), HSR deployment and construction will most likely be drawn to places where there are better infrastructure foundation, better chance to maximize the benefits of the HSR system, and overall more developed regions so that HSR's transformative effect could be maximized. The consequence, however, is also likely a deeply divided and unequal regional economic landscape. The current spatial distribution of HSR stations (Fig. 1) and enormous amount of investment into HSR construction in China, apparently suggests strong policy guidance in the overall development plan of China's HSR. This study applies spatial data analytical methods with county-level socioeconomic panel data from 2008 – 2015 to investigate how the construction of and accessibility to the HSR impacts the county economic development landscape in China. Choosing the county as our analytical unit is mainly because counties often have less say in where an HSR station is to be deployed, analyzing accessibility to HSR at county level might avoid potential endogeneity problem as suggested in many studies (Chen and Vickerman, 2017; Ke et al., 2017; Sun et al., 2017; Vickerman, 2018). Formal statistical test with a two-stage least squares fixed effect model has been applied, and the Durbin–Wu–Hausman test suggests that no endogeneity presents between HSR station deployment and county economic development represented by county per capita GDP. This further supports that HSR deployment in China is less of a pure economic decision, at least at the county level.

3. HSR accessibility indices and the socioeconomic dataset from 2008 to 2015

3.1. HSR accessibility indices

Accessibility between places, origins and destinations, and to certain facilities, such as the HSR stations in this study, has been widely studied (Andersson et al., 2010; Cao et al., 2013; Hensher et al., 2012; Jiao et al., 2016; Kim and Sultana, 2015; Liu and Zhang, 2018; Sanchez-Mateos and Givoni, 2012; Shen and Zhao, 2017; Wang et al., 2016b; Xu et al., 2018; Yu et al., 2014; Zhang et al., 2016; Zhong et al., 2014). Depending on how accessibility is defined, measurement of accessibility varies as well. In our current study, we regard accessibility as an inherent attribute of a county. It measures the overall convenience a county is to the HSR system. We do not use economic volume/population count of the origin or destination to weigh the measure as in many transportation studies (Cao et al., 2013; Chen and Haynes, 2017; Liu and Zhang, 2018; Moyano et al., 2018; Wang et al., 2016b; Zhu et al., 2016) so that the measure can be treated as an independent attribute of the county. The simplest measure of accessibility would be a binary presence/absence designation. Counties that have at least an HSR station in it will be assigned the value 1 (or if there are multiple stations, the count of stations can be used as the value as well), and counties that do not have a station 0 (*pre/abs*). This approach is straightforward and can be done within a GIS without much calculation. Early studies in transportation policy and economics often take this route (Diao, 2018; Sun and Mansury, 2016; Urena et al., 2009). Presence/absence measure is easy to understand. It does not fully capture the connotation of a county's accessibility to the HSR system because a zero would ultimately suggest that the county has "no" access to the HSR system, though the analytical approaches employing this measurement strategy do not necessarily take the meaning. In our analysis, we plan to use this presence/absence strategy at the global modeling level to have a general idea of how presence/absence of an HSR station within a county might impact its economic development after controlling other factors.

In addition to the presence/absence index, we also propose three distance based HSR accessibility indices. The first one measures the Euclidean distance from a county's geometric center to the nearest HSR station (it might or might not locate within that county, *Dist*). We realize the geometric center might not be the best representation of a county's potential origins to initiate the trip to any HSR station. Our current data, however, does not have the required precision to derive a better representative origin. This remains an area that we intend to explore in the future. The second one is a road network travel time measured accessibility (*TravelTime*). Specifically, we have obtained two road network layers of all the possible roads in China in 2012 and 2016. The road network layers contain expressways (including ramps), national road, provincial road, county road and intercity roads. Based on the *Technique Standard of Highway Engineering* released by China's Ministry of Transport in 2004 (Zhang et al., 2016), each grade of road has its own allowed speed limit. We modified the standards slightly based on the more recent road traffic regulations. Specifically, the speed limit for expressways is 100 km/h, for national roads 70 km/h, for provincial roads 50 km/h, for county roads and expressway ramps 40 km/h, and for intercity roads 30 km/h. Though we tried to obtain the road network layers for other years from 2008 to 2015, we were not successful. For this matter, we can only generate approximate travel times for other years than 2012. Specifically, for the years from 2008 to 2012, we used the 2012 road network layer to generate the travel time. For the years from 2013 to 2015, we used the 2016 road network layer to generate the travel time. Calculation of the travel time was done in ArcGIS Pro® using its origin-destination network analyst tool set. The estimated travel time is by no means accurate because of the lack of data. As a measure of relative accessibility to HSR and how it changes over time, however, the measure shall suffice the analysis since the change is roughly consistent over the study period even when only two years of the road network were used. The third measure of HSR accessibility attempts to combine the Euclidean distance and the binary assignment strategy. We term this index the HSR impact index (*HSRImp*). In particular, we will assign 1 to a county that has at least one HSR station within its border. We will then calculate the average distance from those counties' geometric centers to their nearest HSR stations across all years and use that distance as a benchmark distance (d_b). For any other counties that do not have an HSR station within it, we calculate the distance from that county's geometric center to the nearest HSR station ($d_{i\text{-}near}$). We then calculate $d_b/d_{i\text{-}near}$. If the quotient is more than one, a one is assigned to that county (because $d_{i\text{-}near}$ is shorter than the benchmark distance d_b). Otherwise, the quotient is used as the *HSRImp* index.

3.2. The panel dataset of socioeconomic factors from 2008 to 2015

Out of the 2850 (by 2015) county level administrative units in China, some of them are districts under direct prefecture administration. By combining those districts together, we have obtained 2285 analytical units that contains 10 socioeconomic indicators. These include the per capita GDP (*gdppc*), urbanization rate (*urb*), local labor participation rate (*lpr*), local fixed asset investment (*fai*), local government fiscal revenue (*rev*), local government fiscal expenditure (*exp*), year-end residents' total bank deposit (*dep*), the number of students in secondary schools (*stud*), population density (*popden*), and industrialization rate (*ind*). Per capita GDP is used as an indicator to measure a county's economic development and performance. It is measured in current price RMB Yuan. This index can be loosely approximated as the output of the county economic system that depends on all the other inputs as in a production function (Yu, 2006). Urbanization rate is calculated as the ratio between urban population and total population. Local labor participation rate is calculated as the ratio between total employed population and total population. Local fixed asset investment is used to measure the potential of local government's infrastructure maintenance and upgrading capability; it is measured in 10,000 RMB Yuan. Local governmental fiscal revenue represents the county's fiscal healthiness; it is measured in 10,000 RMB Yuan. Local governmental fiscal expenditure measures the county's self-supporting capability; it is measured in 10,000 RMB Yuan. Year-end residents' total bank deposit represents the county's potential for self-sustained development; it is measured in 10,000 RMB Yuan. The number of students in secondary school represents the potential lack of able labor forces, which could adversely impact local economic development. Population density is calculated as the number of persons per square kilometer. Industrialization rate is calculated as the ratio between the added values in the manufacturing sector and GDP.

The data is assembled from the annual *China's County Statistical Yearbook* (2009–2016) and supplemented by *China's Urban Construction Yearbook*. Summary of the socioeconomic data and the three HSR accessibility indices (excluding the binary index) is reported in Table 1.

With the prepared data, we have conducted a variety of preliminary analyses through multiple scatterplots between per capita GDP and the determinants, mainly to determine the possible relationships between per capita GDP and other socioeconomic factors and the four HSR accessibility indices. The preliminary analyses suggest a semi-log-log relationship between GDP and other factors and HSR accessibility indices might provide the better fitting. This preliminary analysis also roughly agrees with an approximate production-function like specification between the output (GDP per capita) and inputs (the socioeconomic factors and accessibility to the HSR system). For this reason, using GDP per capita instead of other measures such as annual GDP growth rate might be more appropriate.

In particular, for the binary presence/absence index (*pre/abs*) and the HSR impact (*HSRImp*) measure, the relationship takes this form:

$$gdppc = e^{\beta_1 urb} \times e^{\beta_2 lpr} \times fai^{\beta_3} \times rev^{\beta_4} \times exp^{\beta_5} \times dep^{\beta_6} \times stud^{\beta_7} \times popden^{\beta_8} \times e^{\beta_9 ind} \times e^{(accessibility)\beta_{10}} \tag{1a}$$

where *accessibility* is either *pre/abs* or *HSRImp*.

For the travel time and Euclidean distance, the relationship takes this form:

$$gdppc = e^{\beta_1 urb} \times e^{\beta_2 lpr} \times fai^{\beta_3} \times rev^{\beta_4} \times exp^{\beta_5} \times dep^{\beta_6} \times stud^{\beta_7} \times popden^{\beta_8} \times e^{\beta_9 ind} \times accessibility^{\beta_{10}} \tag{2a}$$

where *accessibility* is either the road network travel time or Euclidean distance.

Taking a natural logarithm transformation of Eqs. (1a) and (2a)

Table 1
Summary of the socioeconomic panel data and HSR accessibility indices.

	Minimum	1st Quantile	Mean	Median	3rd Quantile	Maximum
gdppc	16.30	12,988.20	21,414.10	32,554.30	37,741.60	331,519.30
urb	0.01	0.13	0.19	0.27	0.31	1.00
lpr	0.00	0.46	0.53	0.54	0.60	5.64
fai	1	12,724	314,536	1,194,696	1,148,983	130,480,000
rev	2	1,008	21,951	161,426	81,559	54,645,164
exp	0	3,424	125,157	270,309	251,255	60,281,711
dep	6	10,783	260,712	1,243,936	925,826	239,139,670
stud	5	610	8,769	19,714	25,622	4,640,000
popden	0.12	100.65	234.00	377.98	530.33	13,359.73
ind	0.02	0.35	0.46	0.45	0.56	1.48
Distance	946	68883	168614	389048	485693	3410600
TravelTime	0.003	85.65	196.26	698.73	896.07	6821.20
HSRImp	0.004	0.03	0.08	0.20	0.22	1.00

yields the familiar linear regression forms. The models can then be estimated with panel regression analytical approaches. As aforementioned, since our data is assembled over geographic units (county level administrative units), ordinary least squares-based estimator, such as the least squares dummy variable (LSDV) model might not be appropriate because the regression residuals are spatially autocorrelated. The source of the residuals' spatial autocorrelation can either be a spatially autocorrelated dependent variable or the spatially autocorrelated error terms because of missing spatially autocorrelated independent variables. Test of the regression residuals' spatial autocorrelation via Lagrange Multiplier could suggest an appropriate specification (Elhorst, 2014). This model is called a global model because it assumes the relationships between the economic performance and its determinants remain the same everywhere. We will estimate the global model with pre/abs as HSR accessibility index.

More importantly, as this investigation intends to explore the potential spatially varying relationships between county's economic development and HSR accessibility, we apply the newly developed geographically weighted panel regression model (Cai et al., 2014; Yu, 2010, 2014) on the other three specifications. This model is a local model because the assumption of fixed relationships everywhere is relaxed. The next section details the geographically weighted panel regression (GWPR) methodology used in this study.

4. The geographically weighted panel regression method

The geographically weighted panel regression (GWPR) method is a direct extension of the cross-sectional geographically weighted regression method (Fotheringham et al., 2002) to estimate spatially varying coefficients (spatial non-stationarity) with panel data. The method was first proposed in Yu (2010) and Yu (2014), and late applied in Cai et al. (2014) to study the spatially varying responses of corn yields to weather conditions. The method follows closely the cross-sectional GWR's rationale and estimation procedures. Just as the cross-sectional GWR, the GWPR method is also an exploratory approach that explores the potential spatially varying relationships. The best use of GWPR is not to make confirmatory statements but to provoke deeper investigation into the potential spatially nonstationary relationships over the span of both the geography and time.

A typical panel regression model takes this form (in matrix form):

$$\mathbf{y}_{1:T} = \mathbf{X}_{1:T}\boldsymbol{\beta} + \mathbf{IN}_{1:T}\boldsymbol{\gamma}_{IN} + \mathbf{TM}_{1:T}\boldsymbol{\gamma}_{TM} + \varepsilon_{1:T},\ \ \varepsilon_{1:T} \sim N(0_{1:T},\ \sigma^2\mathbf{I}_{1:T}) \qquad (1)$$

where $\mathbf{y}_{1:T}$ is the vector of outcome variable (per capita GDP in our study) stacked over T time periods. $\mathbf{X}_{1:T}$ is the matrix of explanatory variables, including an intercept. $\boldsymbol{\beta}$ is the vector of coefficients that is assumed to be spatially nonvariant. $\mathbf{IN}_{1:T}\gamma_{IN}$ captures individual observation specific effects that is invariant over time, and $\mathbf{TM}_{1:T}\gamma_{TM}$ captures temporal specific effects that is invariant over individual observations (Greene, 2003). σ^2 is the variance. Depending on whether γ_{IN} and/or γ_{TM} are assumed to be fixed or random, different estimation approaches can be applied (Greene, 2003). For shorter panels (the number of temporal units is less than the number of parameters), often a random effect model might produce too large variances to have stable estimations. The current development of GWPR, though accommodates random effect model, focuses primarily on fixed effect models because we have relatively shorter temporal dimension.

For fixed effect model, the estimation is often carried out through the fixed effect least squares dummy variable (LSDV) estimator (Baltagi, 2005; Croissant and Millo, 2019) which applies the OLS estimator over the time and/or individual demeaned data. The GW version of the panel model assumes the $\boldsymbol{\beta}$s in Eq. (1) is spatially varying:

$$\mathbf{y}_{1:T} = \mathbf{X}_{1:T}\boldsymbol{\beta}_{(u_i,v_i)} + \mathbf{IN}_{1:T}\boldsymbol{\gamma}_{IN} + \mathbf{TM}_{1:T}\boldsymbol{\gamma}_{TM} + \varepsilon_{1:T},\ \ \varepsilon_{1:T} \sim N(0_{1:T},\ \sigma^2\mathbf{I}_{1:T}) \qquad (2)$$

(u_i, v_i) is the coordinates of location i. For fixed effect, time and/or individual demeaning could essentially make Eq. (2) similar to a cross-sectional setting in that we do not have to worry about the individual effects anymore (Cai et al., 2014). Apparently, this also implies that the inherent data generating spatial process does not change over time or individual. For individual geographical units, this is understandable. For the temporal dimension, however, this might only be applicable for a relatively short period. For this reason, the current development of GWPR is restricted to relatively short panel. Estimation of Eq. (2) has either a parsimonious problem if we have more explanatory variables than the time periods (such as in the current study) since we now have more than $N * T$ unknown parameters ($\boldsymbol{\beta}_{t,(u_i,v_i)}$ s and σ^2) but only $N * T$ observations, or a collapse problem if we have more temporal periods than the explanatory variables because the GWPR model essentially collapses to a collection of time series models at each county. In other words, if $\boldsymbol{\beta}$ is assumed to vary over geographic space, then in the most extreme case we can estimate the $\boldsymbol{\beta}_{(u_i,v_i)}$ using just each location's temporal data for series estimation, which is apparently not what GWPR would intend (this is a typical scenario of overfitting, by assuming the geographic variation is essentially individual variation). To avoid these problems, following the steps of estimating cross-sectional GWR models, we propose the estimation of GWPR model with three steps:

First, a kernel function is selected to mimic the data generating spatial process: $k = f(d, b)$, where d is the spatial distance, and b is a bandwidth parameter. The symmetric Gaussian family kernel functions often work well in actual practices (Fotheringham et al., 2002). The kernel function with the bandwidth parameter is used for two purposes. For one thing, it will create a local sample that is of the right size for any individual so that spatial effects (spatial autocorrelation in the regression residuals) are kept at potential minimum, and there is no parsimonious or collapse problem. For another, the kernel function will also assign distance-decaying weights to any observations that fall within the area determined by the bandwidth. For instance, a typical bi-

Table 2
Regular individual fixed effect panel regression results and tests.

	Estimate	Std. Error	t-value	Pr(> |t|)
urb	−0.037	0.022	−1.643	0.100
lpr	0.375	0.029	12.977	0.000
fai	0.066	0.004	18.354	0.000
rev	0.143	0.007	19.612	0.000
exp	0.054	0.008	6.523	0.000
dep	0.055	0.006	8.838	0.000
stud	−0.264	0.005	−48.577	0.000
popden	0.043	0.010	4.170	0.000
ind	0.236	0.033	7.150	0.000
Presence/absence of HSR station	0.051	0.010	5.054	0.000

Total observations: 2285, years: 8
Total Sum of Squares: 2214.3
Residual Sum of Squares: 856.62
R-Squared: 0.61315
Adj. R-Squared: 0.55763
F-statistic: 2533.58 on 10 and 15985 DF, p-value: < 2.22e-16
Local Robust Lagrange Multiplier test for the lag specification:
LM = 1971.8, df = 1, p-value < 2.2e-16
Local Robust Lagrange Multiplier test for the error specification:
LM = 111.28, df = 1, p-value < 2.2e-16

square kernel function and how it assigns weights to observations takes the form:

$$w_{ij} = \begin{cases} [1-\left(\dfrac{d_{ij}}{b_i}\right)^2]^2, & d_{ij} < b_i \\ 0, & d_{ij} \geq b_i \end{cases} \tag{3}$$

where w_{ij} is the weight assigned by the bi-square kernel function to observations at location j, which is determined by the bandwidth b_i of the kernel function at location i and the distance apart between i and j, d_{ij}. Following the spirit of the First Law of Geography (Tobler, 1970), it is possible that every location in the entire dataset can potentially contribute to the estimate of any location's local coefficients. In practice, however, locations that are too far apart (larger than the bandwidth in the bi-square scenario) might contribute too little to be useful.

Second, from Eq. (3), we can see that there are potentially many choices for the bandwidth (b_i) for any location. To choose the right size for a location's local sample, we need to consider a variety of options. In the cross-sectional scenario (Fotheringham et al., 2002), a leave-one-out cross validation score (CV) or an asymptotic Akaike Information Criterion (AIC) is used as criterion to determine an "optimal" bandwidth. In this investigation, we adopted the leave-one-out cross validation score to obtain the "optimal" bandwidth. An asymptotic Akaike Information Criterion for panel regression based on the demeaned residuals at each location is also considered. The asymptotic AIC takes the form:

$$aAIC = 2 \times p + nT \times [\log(2\pi) + ssq + 1] \tag{4}$$

$$ssq = \log(\sum_{i=1}^{nT} \frac{resid^2}{nT}) \tag{5}$$

where *resid* contains the T residuals at each location, n is the number of geographic locations, T is the number of temporal periods. p is the number of parameters. The results, however, suggest that if the spatial process is considered to be constant over the temporal period, the *aAIC* score will always produce the overfitting result in that the least possible number of local samples will be generated and the GWPR practically reduces to a collection of time-series analyses. For this reason, the current study relies on selecting the optimal bandwidth using the leave-one-out cross-validation only as detailed in Yu (2006) and Cai et al. (2014). From the cross-sectional GWR's experience, there are two options when selecting the optimal bandwidth, namely, a fixed bandwidth option and an adaptive bandwidth option. The fixed bandwidth option will produce a fixed bandwidth value (b) that is the same for every location ($b_i = b_j$). This option is fast. It is best used for data sets that are collected over regularly spaced geographic units such as remote sensing images or other regular tessellations. For irregularly spaced geographic units as is common in socioeconomic studies, the fixed option might produce too much variance in places where observations are sparse but mask subtle changes in places where observations are dense (Fotheringham et al., 2002). For this reason, the adaptive option is often used for irregularly spaced geographic units. Instead of finding one optimal bandwidth, the adaptive option attempts to find the same number of local samples for each location by varying the bandwidth at each location. A golden-section search optimization algorithm (Fotheringham et al., 2002) is used to find the bandwidth or the same number of nearest observations that produces the smallest *cross-validation score*.

Third, for each individual observation, once the kernel function, the fixed or adaptive strategy are determined and put to work, a local sample with the right size and distance-decaying weighted "observed" values will be acquired. The regular panel fixed effect estimation can be applied to these weighted local samples to produce the unique set of coefficients $\boldsymbol{\beta}_{(u_i,v_i)}$ and residuals for that individual location (i). The process will be repeated for every location to obtain the full set of spatially varying $\boldsymbol{\beta}$. Asymptotic (pseudo) inferential statistics (the p-values) can also be produced to explore the estimated relationships (with caution).

5. Results and discussion

The model with the presence/absence HSR accessibility was fitted through a regular fixed effect panel regression. We also performed the local robust Lagrange Multiplier (LM) tests for the residuals' spatial autocorrelation (Elhorst, 2014). The results are reported in Table 2. The LM tests clearly suggests that there is significant spatial autocorrelation in the residuals. The LM tests also suggest that the spatial lag specification (with the lagged dependent variable as an added explanatory variable) might be more appropriate (Elhorst, 2014). A spatial lag specification is then assumed and estimated. The results are reported in Table 3.

The geographically weighted panel regression model is applied to the other three models with Euclidean distance, road network travel time and HSR impact each serving as the index for the HSR accessibility measure. Using the criterion of finding the lowest cross-validation score and an adaptive bandwidth searching strategy as detailed in the method section, the algorithm was able to identify 235 (out of 2285) local samples when using Euclidean distance as proxy for HSR accessibility; 59 local samples when using road network travel time as proxy for HSR accessibility; and 52 local samples when using HSR impact as proxy for HSR accessibility. All the above estimation is done in R (R Core Team, 2019), with packages spdep (Bivand and Piras, 2015), plm and splm

Table 3
Spatial lag specification panel estimation.

	Estimate	Std. Error	t-value	Pr(> |t|)
urb	−0.021	0.017	−1.206	0.228
lpr	0.288	0.023	12.801	0.000
fai	0.029	0.003	10.225	0.000
rev	0.079	0.006	13.865	0.000
exp	0.011	0.006	1.687	0.092
dep	0.012	0.005	2.405	0.016
stud	−0.111	0.004	−25.081	0.000
popden	0.056	0.008	6.982	0.000
ind	0.437	0.026	16.964	0.000
Presence/absence of HSR station	0.027	0.008	3.348	0.001
Spatial autoregressive coefficient	0.578	0.007	80.676	0.000

Total observations: 2285, years: 8
Conditional R-squared: 0.8972
Adjusted conditional R-squared: 0.8824

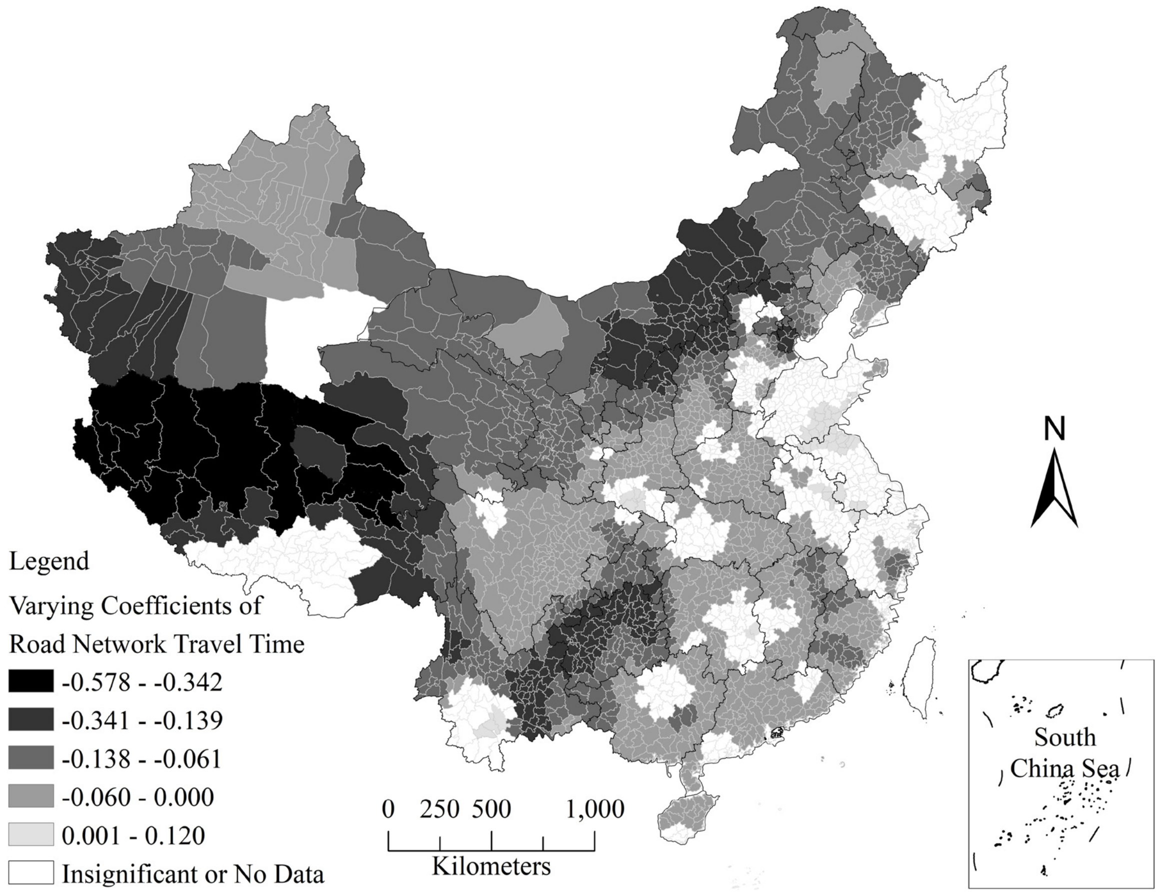

Fig. 2. Spatially varying coefficient of HSR accessibility, measured by road network travel time.

(Croissant and Millo, 2019), and the GWPR scripts written by the first author. After controlling for the other socioeconomic variables, the potentially spatially varying relationships between HSR accessibility and county level economic development with the three different indices are mapped out in Figs. 2–4. In the maps, only the county whose coefficients are significant at 95 % (pseudo-)confidence level and above are gray scaled. The non-significant ones (and the ones without data) are whited out.

The results presented in the tables and maps agree well with our hypotheses that more convenient access to the HSR system (through accessibility measures to the HSR stations) tends to facilitate a county's economic performance. The spatial autocorrelation tests presented in Table 1 also attests that analysis with geographic data likely needs spatial approaches as detailed in Elhorst (2014) and argued previously in the current study. In particular, we have a few detailed discussion items to present.

First, when the spatial effect was not controlled (Table 1), the model suggests that per capita GDP in a county with at least an HSR station within its border is about 5.2 % more than a county without an HSR station within, *ceteris paribus*. Once the spatial effect was controlled (Table 2), however, the number dropped to 2.7 %. The relationship is statistically significant in the spatial autoregressive model. The result suggests that construction of HSR provides clear advantage for a county's economic performance, at least from a global, averaged perspective. The gain is not enormous, but it does support the rationale the Chinese government employs to develop China's HSR system. As argued previously, the immediate return of HSR construction is likely no match to the initial investment. The intention of constructing HSR system, however, is more likely to encourage the development of underdeveloped regions and provide long-term social and economic benefits to promote more balanced regional development in China. The results also suggest that if spatial effects are not considered, the estimation is likely inflated, which could give erroneous impression of the effects of HSR. Still, using HSR construction as a local economic development booster seems to work during the period from 2008 – 2015. Whether or not the benefit will hold in the long run, however, the global model does not provide an answer.

Second, the results from the GWPR models provide rich amount of information. From comparing the three maps, we do not have a distinctive impression as to which HSR accessibility measure might provide a more reasonable representation of HSR accessibility. Though details vary from map to map, the general pattern of significance remain similar across all three maps. For instance, cross comparing Figs. 2–4 with Fig. 1, we can see that in the east coastal counties (mainly in Shandong, Jiangsu, Anhui, Shanghai and Zhejiang) where HSR stations are most densely distributed, the relationships between HSR accessibility and counties' economic performance are not (pseudo) significant. The counties that show pseudo statistical significance and strong relationships between accessibility to HSR system and counties' economic performance are mainly in the West (Tibet, Yunnan, Guizhou, Gansu, Ningxia, Qinghai, Shaanxi, Xinjiang) and the North (Inner Mongonia, Shanxi). Counties in some of the Central provinces (Hunan, Henan, and Jiangxi) and even Guangdong and Fujian also show significant though weak relationships between HSR accessibility and counties' economic development. The three maps provide solid evidence that most relatively underdeveloped areas in China benefit from more convenient access to the HSR system with varying degrees. Of the three maps, it seems that HSR accessibility measured by road network travel time and Euclidean distance produces more similar results than the HSR impact index. As aforementioned, the HSR impact index is a combination of the presence/absence measure and the Euclidean distance measure. The designation of HSR impact as 1 if a county has an

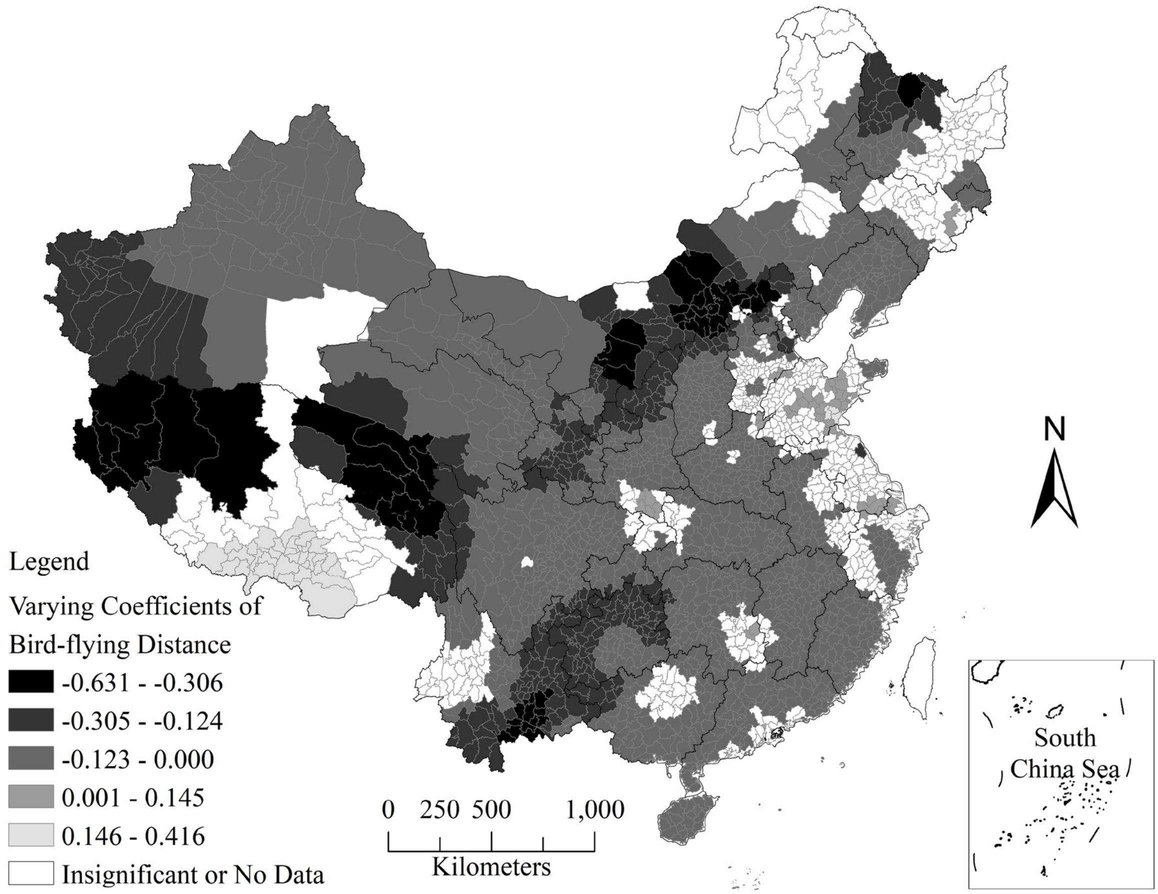

Fig. 3. Spatially varying coefficients of HSR accessibility, measured by bird-flying distance.

HSR stations within or if a county to its nearest HSR station is sufficiently close ($d_{i\text{-}near}$ is equal to or shorter than the benchmark distance d_b) and $d_b/d_{i\text{-}near}$ otherwise (see Section 3.1 for details), seems to have a converging effect. We contend that this is because when more HSR stations are deployed, this index will become increasingly less varying. Still, all three indices perform sufficiently satisfactorily in revealing similar patterns, which suggests our analytical results are robust against different HSR accessibility indices.

When using the road network travel time as the HSR accessibility measure, the map (Fig. 2) suggests that in the most extreme cases (the most remote rural counties in Tibet, and some rural counties in Guizhou, Yunan and Inner Mongolia), a 10 % reduction in travel time from the county's geometric center to its nearest HSR station could result in 1.3%–5.6% increase of per capita GDP. When using the Euclidean distance as the HSR accessibility measure, the map (Fig. 3) suggests that in the most extreme cases (similar areas as in Fig. 2), a 10 % shorter of the distance from the county's geometric center to its nearest HSR station could result in 1.2%–5.8% increase of per capita GDP. Using the HSR impact as the HSR accessibility index, however, suggests that the strongest significant relationships exist in the most remote rural counties in Tibet. As a matter of fact, in the most extreme cases, for counties from its geometric center to the nearest HSR station, every 1% closer to the benchmark distance (d_b), the county's per capita GDP could increase as much as 38.1%–74%. Considering those are the counties in the most remote areas in Tibet, per capita GDP there might fluctuate quite drastically. For the majority of other counties, though, every 1% closer to the benchmark distance, per capita GDP increase anywhere from 1% to 10 %. Still, such a large fluctuation might suggest the HSR impact measure could be an unstable measurement for HSR accessibility.

Third, though the performance of the three HSR accessibility indices differs in relating access to the HSR system and county's economic development, one common pattern is salient. That is, the benefit of easier access to the HSR system diminishes as the density of HSR system and services increase. All three maps reflect such a pattern in various degrees. The patches of counties in the east coastal region that do not show pseudo significance is where HSR density is the highest (and deployed the earliest) and counties with highest urbanization rate (less rural areas). This is clear evidence of HSR system's diminishing marginal effect. The diminishing marginal effect might also suggest the benefit of HSR construction and deployment is transformative. When an area was relatively new to have HSR access, construction and deployment of HSR in this area render the highest benefit. Once the density of HSR increases and access to HSR system becomes more frequent, the direct benefit brought to local economic development by the HSR system starts to diminish. Local economic develop starts to benefit from other factors such as increased investment, increased labor participation and upgraded industrial structure that are brought by the construction and deployment of the HSR system (Diao, 2018). For illustration purposes, we produce the spatially varying coefficient map for fixed asset investment (in relation to county's per capita GDP) when using road network travel time as the proxy for HSR accessibility (Fig. 5). Cross-compare Figs. 5 and 2, the supplementary patterns of these two factors are quite telling. In counties where access to HSR's support to local development is no longer significant, fixed asset investment shows significant positive support for local economic development (such as in the East coastal counties and Northeast counties). As proposed in Cheng et al. (2015) and Vickerman (2018), this shift is likely a reflection of HSR's wider economic impact and transformative effect to local economy. More importantly, for rural counties in West China (specifically Tibet, Guizhou, and Yunnan), we also found that both access to the HSR system and the investment are supporting local

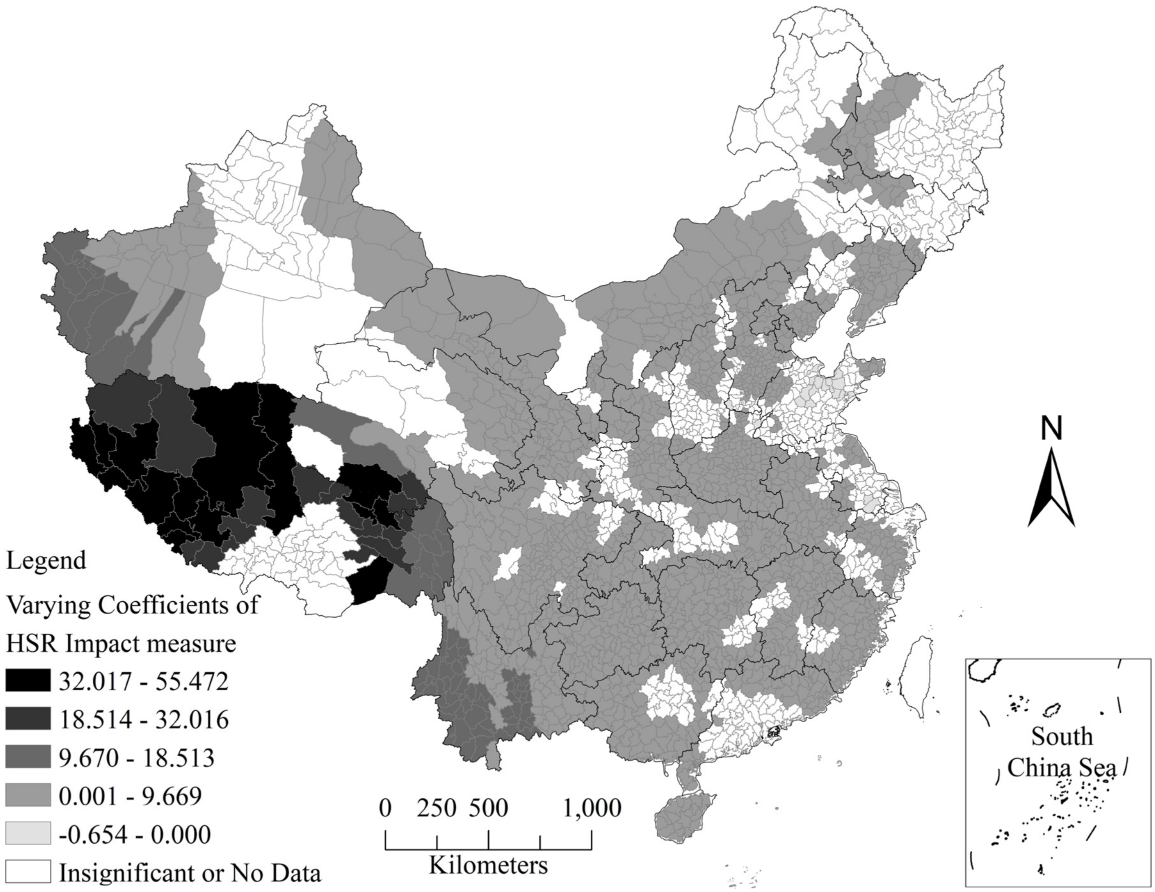

Fig. 4. Spatially varying coefficients of HSR accessibility, as measured by HSR impact.

development. Such mutual reinforcement might suggest the HSR is indeed bringing more production factors to the relatively under-developed rural areas. This further supports that one of Chinese government's intentions to construct and deploy HSR system is to reduce regional inequality. The patterns presented through the exploratory GWPR approach also provide possible answers to the question "does growth follow the rail" (Diao, 2018). The maps seem to suggest that growth does follow the rail, albeit the growth has a diminishing marginal return. The transformative effect and wider economic impact of the HSR, however, suggests that construction and deployment of HSR bring more than just convenient access to a modern transportation mode. The ensuing increased fixed asset investment and likely upgraded local industrial structure along with influx of skilled labor forces, become dominant economic development factors while HSR system's direct benefit is diminishing. We contend that the findings through the exploratory GWPR analysis provide empirical support to the current government's policy of developing HSR to encourage local economic development, especially in the rural areas where economic development lags behind the urban areas. Although HSR's direct benefit is diminishing as accessibility to HSR becomes commonplace, the wider economic impact of HSR is likely what will drive local economic development in the long run. Such wider economic impact might very well be what will sustain the successful implementation of the New Countryside Construction and Greater West Development strategies in China.

6. Conclusion

The current investigation for the first time develops the framework of a geographically weighted panel regression and applies it to assess the relationships between HSR accessibility and county's economic development in China. Although the GWPR approach is relatively new, the results it produces are promising.

The study generates four HSR accessibility indices using GIS and tests the relationship with both a global level analysis (the spatial panel fixed effect lag model) and three local level analyses (the GWPR analysis with three HSR accessibility proxies). On the global level, it seems that construction and deployment of HSR system is beneficial to local economic performance. A county with an HSR station within is on average 2.7 % higher in per capita GDP than a county without. On the local level, however, depending on which index is used, the results are different but robust in terms of patterns revealed. For the road network measured accessibility, every 10 % reduction of travel time from a county to its nearest HSR station results in 1.3%–5.6% increase in per capita GDP. If HSR accessibility is measured with simple Euclidean distance, then every 10 % reduction of Euclidean distance from a county to its nearest HSR station could result in 1.2%–5.8% increase of per capita GDP. The measure that we termed HSR impact that combines the binary presence/absence measure and a distance measure, however, produces some rather unstable results which might suggest the measure is not as effective an accessibility measure as the other two measures.

Still, evaluating a county's HSR accessibility and how it impacts county's economic development in China with a GWPR approach seems to address some theoretical debates over the benefits and effects of construction and deployment of HSR in China. We contend that the exploratory approach GWPR supplies evidence supporting the wider economic impact and transformative effect of HSR in China's case for county development. The maps produced by GWPR also agree that the development (in China at county level) indeed follows the rail (high-speed rail). The benefit of the HSR on local development, however, is diminishing as accessibility saturates. The policy implication from the current study suggests that further deployment of HSR, especially into

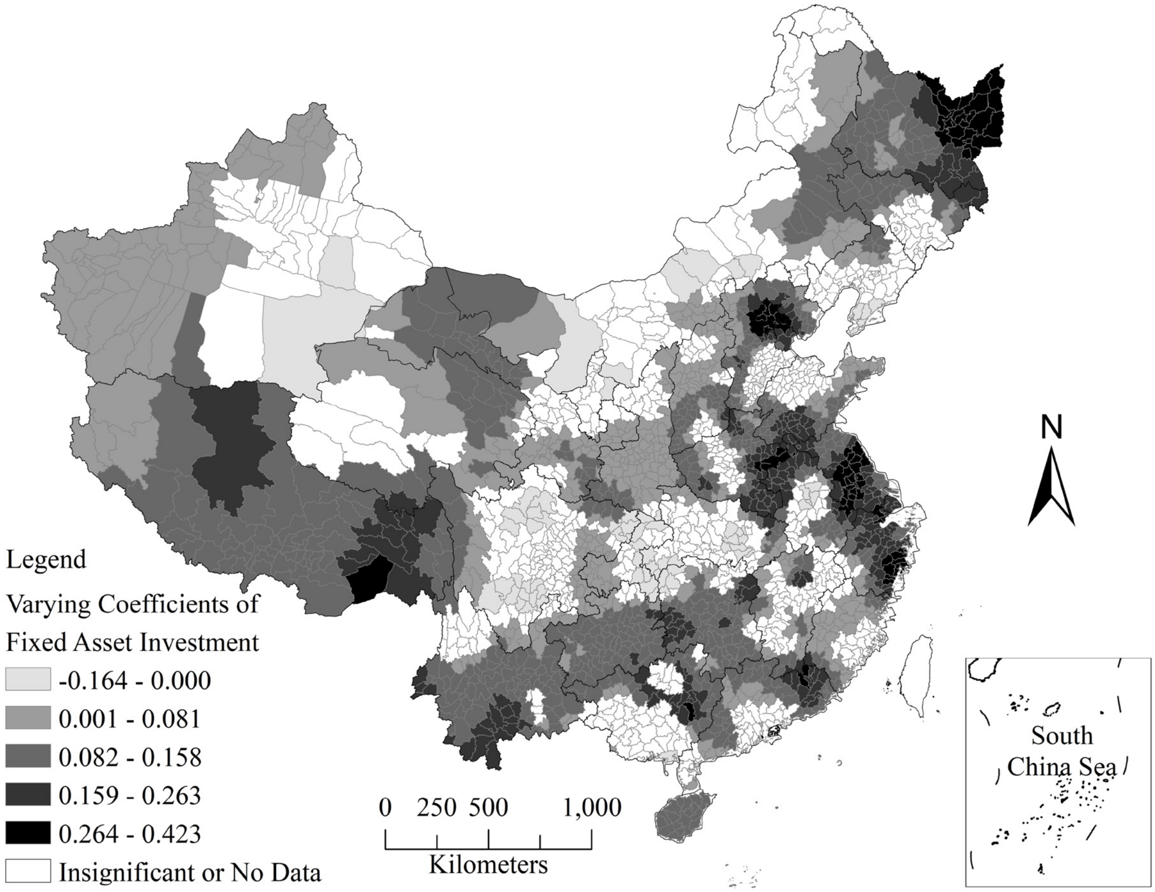

Fig. 5. Spatially varying coefficients for fixed asset investment, with road network travel time as HSR accessibility measure.

the relatively less HSR accessible North (Inner Mongolia) and West (Xinjiang, Tibet, Yunnan, and Guizhou), could result in immediate economic benefits. This is important for the implementation of the New Countryside Construction and Greater West Development strategy to promote a relatively balanced regional development landscape in China. As accessibility to HSR becomes more frequent, however, these regions will still benefit from the possible wider economic impact and transformative effect brought because of HSR construction and deployment there.

The development of the GWPR methodology is still in its early stages. Estimation of more complex model with other effects (such as time fixed effect, random effect) is under development. The results from the GWPR, similar as with its cross-sectional counterpart, GWR, shall be used with caution as the model uses observations repetitively. Inference from the model is not likely as strong as with confirmatory analysis. Still, the potential of GWPR to explore spatially varying relationships using panel data merits further investigation. We intend to develop the method to provide more complete analysis capability in the future.

CRediT authorship contribution statement

Yu Danlin: Data curation, Conceptualization, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Writing - original draft, Writing - review & editing, Visualization, Supervision. **Zhang Yaojun:** Conceptualization, Investigation, Resources, Writing - original draft, Supervision. **Wu Xiwei:** Data curation, Resources. **Li Ding:** Data curation, Resources. **Li Guangdong:** Data curation.

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