

Evaluation of the land value-added benefit brought by urban rail transit: The case in Changsha, China

Wenbin Tang (corresponding author)
Changsha University of Science and
Technology
wbtang2003@163.com

Qingbin Cui
University of Maryland
cui@umd.edu

Feilian Zhang
Central South University
zfl@mail.csu.edu.cn

Hongyan Yan
Hunan University of Finance and Economics
yanhongyan82@163.com

Abstract: Accurate evaluation of land value-added benefit brought by urban rail transit (URT) is critical for project investment decision making and value capture strategy development. Early studies have focused on the value impact strength under the assumption of the same impact range for all stations. However, the value impact range at different stations may vary owing to different accessibilities. Therefore, the present study releases this assumption and incorporates the changed impact range into the land value-added analysis. It presents a method to determine the range of land value-added impact and sample selection using the generalized transportation cost model, then spatial econometric models are further developed to estimate the impact strength. On the basis of these models, the entire value-added benefit brought by URT is evaluated. A case study of the Changsha Metro Line 2 in China is discussed to demonstrate the procedure, model, and analysis of spatial impact. The empirical analysis shows a dumbbell-shaped impact on the land value-added benefit along the transit line with a distance-dependent pattern at each station. In addition, the land value-added benefit from Changsha Metro Line 2 reached 12.099 billion USD. Lastly, two main value-added benefit capture modes are discussed, namely, land integration development and special land tax.

Keywords: Urban rail transit, land value-added, externalities, generalized traffic cost model, spatial econometrics

Article history:

Received: August 4, 2019
Received in revised form:
October 8, 2020
Accepted: February 11, 2021
Available online: May 7, 2021

1 Introduction

At present, emerging countries and regions are ushering in a golden period of urban rail transit (URT) construction. Many Asian countries, including China, India, Iran, Vietnam, and Indonesia, are vigorously developing URT. In China, for example, 176 URT planning lines are expected in the next 10 years with a total mileage of 6,200 km, and construction investment will exceed 300 billion USD.

URT projects are found to be generally facing difficulties in financing, low investment efficiency, and even negative revenues. The following Chinese cities are cited as examples. In 2016, the operating

loss of Nanjing Metro was more than 210.8 million USD (225.4 km); the operating loss of the Beijing Metro was approximately 301.2 million USD (554 km); the operating loss of Shenzhen Metro was near 150.6 million USD (178.4 km). Therefore, the local governments need to bear all or part of these losses through providing subsidies to maintain the normal operation of the metro companies. According to the traditional decision-making method, these projects are at a large loss and the investments are failed. However, why are numerous cities still dedicated to developing URT?

In fact, as a quasi-public good, URT project investment has brought remarkable external benefits to the city's economy (Litman, 2007), for example, it can promote land appreciation, save travel time and improve travel comfort; it can also reduce automobile dependency and solve the problem of urban traffic congestion, reduce urban pollution and the construction of public infrastructure, such as urban roads and parking lots; moreover, it can save energy and land resources, mitigate climate change, bring more social employment opportunities and promote regional economic and social development. Among them, the most beneficial one is the land appreciation (Hess & Almeida, 2007). However, such benefit is occupied by real estate owners and users freely, and it is not displayed in the financial statements of the URT company, thereby challenging the traditional measurement methods of project investment benefit.

Many governments encourage private capital to participate in the investment of URT to alleviate the increasing pressure on financial subsidies. Indeed, private capital chases profit as the most important goal. Hence, accurately assessing the land value-added benefit and vigorously executing internalization strategies of the externalities are critical to solve the above problems.

The present study is structured as follows. Section 2 summarizes the literature on quantitative studies of the land or property value-added impact brought by URT. Section 3 introduces the econometric models of generalized transportation cost model (GTCM) for measuring the impact range, spatial econometric models for measuring the impact intensity, measurement model for the entire benefit of land value-added, and models for value capture. Section 4 reports the Changsha Metro Line 2 in China as a case study. Section 5 discusses the two main modes of external benefits recovery in further.

2 Literature review

As early as the 1970s, European and American scholars found that rail transit could promote the optimized utilization of land and bring obvious value-added benefit to the surrounding property. On the basis of the urban development form, the land rent and price, and the location theories, scholars have made numerous quantitative studies of the land or property value-added impact from URT.

The objects of these studies are involved in the land (Du & Mulley, 2012; Knaap, Ding, & Hopkins, 2001), residential property (Ibeas, Cordera, Dell'Olio, Coppola, & Dominguez, 2012; Zhong & Li, 2016), and office and commercial property (Cervero & Duncan, 2002; Cohen & Brown, 2017). Most of these studies focus on the impact of URT on residential property value because its transactions in the market are generally more than any other property type, and more sample data is available for quantitative study (Mohammad, Graham, Melo, & Anderson, 2013).

The land and property along URT could obtain a positive value growth (Atkinson-Palombo, 2010; Pan, 2013; Yan, Delmelle, & Duncan, 2012). However, other studies found that their value was reduced because their locations were extremely close to the URT; they were also noisy, polluted and with high crime levels (Hui, Ho, & Ho, 2004). Moreover, a few studies concluded the absence of an obvious impact (Clower & Weinstein, 2002). The value-added benefit of land appears to be generally higher than that of property (Mohammad et al., 2013). Similarly, the value-added benefits of office and commercial property are also higher than that of residential property (Weinstein & Clower, 2002). Moreover, com-

muter railways have a relatively higher impact on property value than light rail and metro (Cervero & Duncan, 2002).

From the research methodology, the functional forms used in early literature were diverse, such as hedonic price model (HPM) (Gibbons & Machin, 2005; Pior & Shimizu, 2001), traffic cost model (Weinstein & Clower, 2002), generalized traffic cost model (Chu, Jiang, Li, & Luo, 2016), BP neural network analysis method (Yang & Shao, 2008), and spectral analysis (Su & Feng, 2011). HPM is designed to estimate the implicit value of differences in property characteristics, and it is well suited to estimate the externalized benefits owing to improved accessibility of the land. Hence, it becomes the most common methodology. HPM has been developed from the linear form (McMillen & McDonald, 2004) to the logarithm–logarithm (Golub, Guhathakurta, & Sollapuram, 2012; Wang, Feng, Deng, & Cheng, 2016) and semi-logarithm (Zhang & Xu, 2017) forms.

A basic hypothesis in HPM is that variables and residual of multiple linear regression are independent and irrelevant. However, a strong spatial relationship exists between observations in the real estate market. Such a relationship is reflected in the spatial dependence (or autocorrelation), which means that the observed property values in different geographical spaces are dependent (Ibeas et al., 2012). Therefore, this actual situation might violate the model hypothesis. Macfarlane, Garrow, and Moreno-Cruz (2015), Seo, Golub, and Kuby (2014), Yang, Quan, Yan, and He (2016), and Xu, Zhang, and Aditjandra (2016) introduced the theory of spatial econometrics to improve HPM and avoid biased or inefficient parameters. Moreover, they analyzed the relationship between the property price and proximity to URT. The spatial econometric models based on HPM could calibrate reliable regression parameters and explain well the spatial dependence.

Numerous studies believed that value-added impact was extremely small when the distance to URT station exceeded a certain boundary. In addition, the typical assumptions of impact range were 400 (Xu et al., 2016), 500 (Pagliara & Papa, 2011), 800 (Atkinson-Palombo, 2010), and 1,000 m (Yang et al., 2016) and 1 mi (Yan et al., 2012; Zhong & Li, 2016). Moreover, other studies modeled accessibility variables beyond 1 mi by considering the bike or bus connection, such as 2 (Golub et al., 2012), 3 (Pan, 2013), and 5 mi (Macfarlane et al., 2015); and 3 (Seo et al., 2014) and 6 km (Zhang & Wang, 2013). In these studies, the influence radius of URT and the sample selection range for each station were assumed to be the same. In fact, reachability differs between the areas in the downtown and suburb. Hence, the corresponding radius of land appreciation at each station may not be equal and may exceed 1 mi.

Obviously, previous studies may have certain deficiencies in the calculation of impact range. In recent years, GTCM has been extensively used in the study of rational choice about the most economical and effective travel mode and route (Guo, Zhang, You, Hu, & Pei, 2016). It also provides a new idea for determining the impact scope of URT.

Therefore, the present study attempts to fill the gap in early research by implementing a systematic econometric analysis based on the perspective of external benefits measurement.

3 Methods and models

According to the principle of corridor effect, the impact of URT on the land value should be considered from two dimensions. First is the impact boundary range, which is the maximum distance of the land value-added impact. Second is the impact intensity, which is the increment of land value per unit area. Moreover, it describes the change law of the land value-added effect. Accordingly, the present study builds evaluation models from these two dimensions.

3.1 GTCM for the impact range of land value-added

The nature of the link between urban transport and land use is the complementarities between transport costs and rent (or land value). Therefore, a travel situation in a city according to the principle of accessibility is established as follows. The place P is taken as a starting point, which is located on the impact boundary of the URT station S. The place CBD is taken as the destination, which is located on a city business district (CBD) or workplace. Figure 1 shows that this trip path has two options: to take a traditional bus (including middle transfer) directly from points P to CBD or to walk or ride a bike from points P to S and then change to metro and reach point CBD.

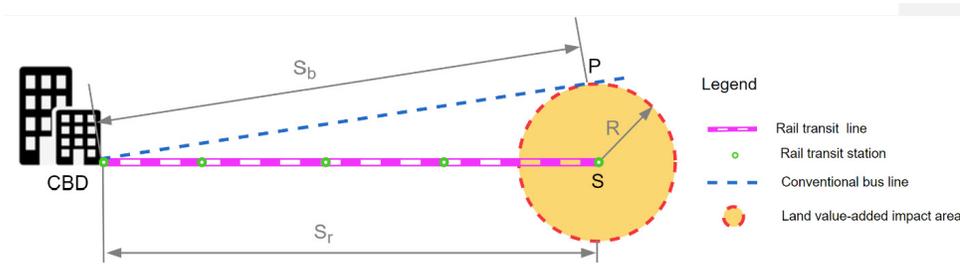


Figure 1. Calculation model for land value-added impact range

If the least travel cost is taken as the criterion for attracting passengers to take URT, then,

$$R/V_w + C_r/k \leq C_b/k \quad (1)$$

where V_w is the walking speed or the bicycle speed from points P to S, C_r is the general transportation cost needed for the URT ride (the distance is S_r), C_b is the general transportation cost needed for the traditional bus ride (the distance is S_b), and k is the time value of the residents.

For a passenger, the total cost incurred during the ride includes not only the actual fare paid, but also the cost of travel time spent in the process (Travel time costs), usually including the time values of the passenger walking to the station, waiting for the bus and taking the bus, and the quality of public transportation services (such as safety, convenience, comfort, etc.). From the above, it can be seen that there are many factors that constitute the generalized cost. Out of the need to simplify the model, usually only a few main factors in the generalized cost are considered in many previous studies, such as fare paid, travel time, waiting time and ride fatigue (Guo et al., 2016). Therefore, the present study constructs the following generalized traffic cost calculation equations:

$$C_b = F_b + \delta \times k \times [(S_u/V_u + S_o/V_o) \times \lambda + t_1 \times n_1] \quad (2)$$

$$C_r = F_r + \delta \times k \times (S_r/V_r + t_2 \times n_2) \quad (3)$$

where F_b is the fare of conventional bus, and F_r is the fare of URT; δ is the work utilization coefficient; S_u and S_o are the downtown and suburb parts of the distance from points P to CBD, respectively, V_u and V_o are the corresponding average speed of conventional bus in the downtown and suburb parts; V_r is the average speed of URT; t_1 and t_2 are the waiting time for traditional bus and for URT, respectively; n_1 and n_2 are the transfer times during a certain trip by traditional bus and by URT, respectively; and λ is the comfort coefficient of URT relative to conventional bus.

3.2 Econometric model for the impact intensity of land value-added

The present study introduces the theory of spatial econometrics into classic HPM to solve the problem of spatial dependence of samples in the real estate market.

3.2.1 Variable selection and description

On the basis of the basic analysis frame of HPM, the present study establishes the index system while completely considering the feasibility of data acquisition and avoiding multi-collinearity. Table 1 shows such a system, which reflects the characteristics of property value attributes from three aspects, namely, location, neighborhood, and structural features.

Table 1. Variable names and descriptions

Variable category	Name of variable	Unit	Variable description
Average price of real estate	<i>Price</i>	¥/m ²	Transaction price
Location feature	<i>DS</i>	km	Distance from real estate to the nearest Metro station
	<i>DCBD</i>	km	Distance from real estate to CBD or workplace
Neighborhood characteristics	<i>Bus</i>	-	Number of bus routes in the community
	<i>PSMS</i>	-	Assign 1 if the key primary or middle school exists within 1 km; assign 0 if otherwise.
	<i>PW</i>	-	Assign 1 if parks or water features exist within 1 km; assign 0 if otherwise.
	<i>Market</i>	-	Assign 1 if a large supermarket exists within 1 km; assign 0 if otherwise.
	<i>Hospital</i>	-	Assign 1 if a large hospital exists within 1 km; assign 0 if otherwise.
	<i>GLR</i>	-	Green land rate
	<i>PR</i>	-	Plot ratio
Structural features	<i>Age</i>	year	Age of real estate
	<i>AS</i>	10,000 m ²	Area of structure
	<i>BS</i>	-	Assign 1 if a slab building or a combination of a slab building and tower block exists; assign 0 if otherwise.
	<i>Floor</i>	-	Assign 1 if a small high-rise or high-rise apartment; assign 0 if otherwise.

Compared with the linear and logarithm–logarithm models, the semi-logarithmic form of HPM has advantages. The relationship between the property price and the “characteristic beam” is nonlinear. Hence, we can directly use the characteristic price coefficient to explain the marginal impact of the independent variable on property price. We can also convert it to the absolute data of the variable change through the anti-logarithmic calculation, and operating this process is more easy. Therefore, the present study chooses the semi-logarithm form of the HPM as the basic econometric model:

$$\ln P = \rho_0 + \rho_1 DS + \rho_2 DCBD + \rho_3 Bus + \rho_4 PSMS + \rho_5 PW + \rho_6 Market + \rho_7 Hospital + \rho_8 GSR + \rho_9 PR + \rho_{10} Age + \rho_{11} AS + \rho_{12} BS + \rho_{13} Floor + \varepsilon \quad (4)$$

where P is the property price, $\rho_0 \dots \rho_{13}$ are the regression coefficients corresponding to each characteristic variable, ε is the random error, and $\varepsilon \in N(0, \sigma^2 I)$.

3.2.2 Spatial lag and error models

Spatial econometric model has multiple types, and the most common are spatial lag model (SLM) and spatial error model (SEM) (Kim & Zhang, 2005). If the spatial test is proven to be prominent, the analysis model can be finally determined according to the dominance of spatial autocorrelation and spatial heterogeneity (Wen, Zhang, & Zhang, 2011).

Spatial lag model

The SLM is used to study the effect of one variable on the same variable in other locations of the entire system. The method for modeling is to eliminate redundancy from a spatial weight matrix representing a high-order adjacent relationship. The basic expression is

$$Y = \lambda WY + X\beta + \xi \quad (5)$$

where Y is a vector ($n \times 1$) corresponding to a dependent variable; β is a vector ($n \times k$) of the parameter corresponding to an independent variable X , ξ is a vector ($n \times 1$) of errors, W is an exogenous spatial weights matrix ($n \times n$), and the spatial correlation coefficient $\lambda \in (-1, 1)$ represents the impact between adjacent areas.

Spatial error model

The SEM is used to study the spatial correlation of residual terms and their disturbance, and the disturbance of residuals shows spatial correlation. The model is shown as follows:

$$Y = X\beta + \xi \quad (6)$$

$$\xi = \lambda W\xi + \varepsilon \quad (7)$$

where ξ , W , ε , and λ are the same as mentioned above, if the value of $|\lambda|$ is high, then, the error term has a prominent spatial effect on the residential property price.

3.3 Measurement model for the land value-added benefit

If the impacted range of the land value-added is divided into n intervals, then, the impact strength on the boundary of each interval $S_j (1 \leq j \leq n)$ will be

$$f(S_j) = e^{\rho_j} - 1 \quad (8)$$

where ρ_{1j} is the regression coefficient of the characteristic variables DS in formula (4); the samples of regression analysis are extracted from the interval S_j .

The impact strength coefficient in the same interval is assumed to be the linear attenuation to simplify the calculation. Hence, the average within the interval S_j is

$$\bar{f}(S_j) = [f(S_j) + f(S_{j+1})] / 2 \tag{9}$$

According to the above assumption, $\bar{f}(S_j)$ will face a downtrend in accordance with the distance to the URT from near to far. Hence, $f(S_{j+1})$ can be assumed to be zero when $j = n$, and the land value-added impact will disappear.

Figure 2 shows that the subdivided land in the j^{th} interval is divided into m pieces.

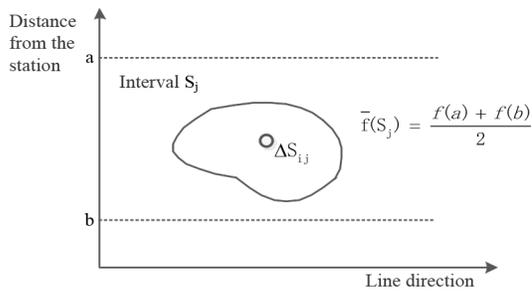


Figure 2. Calculation model for the value-added impact intensity of cell plot

The i^{th} piece of land within the interval S_j is assumed to be S_{ij} ($i = 1, 2, \dots, m, j = 1, 2, \dots, n$). Then, the area of the land value-added impact is ΔS_{ij} , the intensity of the land value-added impact is $\bar{f}(S_{ij})$, and the entire benefit is

$$Y = \sum_{j=1}^n V_j = \sum_{j=1}^n \sum_{i=1}^m \bar{f}(S_{ij}) \times \Delta S_{ij} \tag{10}$$

3.4 Value capture method

URT has been found to have two main modes to capture the benefit from land value-added. The first is the integrated land development mode represented by Hong Kong. The second is the premium recovery mode of special land tax represented by the United States.

3.4.1 Integrated development mode

When the government determines the area of allocated land for integrated development, the calculation formula is

$$A_d = (Y_i \times \tau) / (P_i \times \psi) \tag{11}$$

where A_d is the land area for integrated development; Y_i is the loss of project investment; τ is the proportion of the government subsidies to the project investment loss by the integrated development mode; ψ is the return proportion of land appreciation benefit to URT corporation, and it generally

takes 30% to 50%; P_i is the price appreciation of unit land area.

3.4.2 Special land tax mode

For the undeveloped areas, the remaining land can be taxed when it's in the process of trading except for the land acquired by URT corporation for integrated development. For the developed areas, the land value-added tax can be incorporated into the property tax and will be collected together. The calculation formula is

$$\text{Tax} = \sum S_i \times P_i \times \Phi \quad (12)$$

where i is the serial number of the plot along URT line, correspondingly, S_i is the construction area in developed areas or the land area remaining for commercial development in undeveloped areas, P_i is the price appreciation of unit land area, and Φ is the proportion of taxation on land value-added benefit.

4 Case study

Changsha is located in Central and South China, where traffic location is prominent. It lies on the gold cross of two national high-speed railways: Beijing–Guangzhou and Shanghai–Kunming. In addition, another four national high-speed railways passing here will be built in the future. Changsha has a total urban area of about 2,185 km² and a total population of over 8.39 million (2019). The metro network program of Changsha consists of 12 lines.

As the east-west direction backbone in the URT network, Changsha Metro Line 2 has a total length of about 40 km. It will be constructed in three stages. The first phase engineering project from Wangchengpo to Guangda station has been in operation since April 2014, with a length of 22.262 km. The first phase engineering of the west extension project from West Meixi Lake to Wangchengpo station has been in operation since December 2015, with a length of 4.449 km. The second phase engineering of the west extension project remains in the planning stage. Hence, it is not considered in this study.

4.1 Measurement of the land value-added impact range of Changsha Metro Line 2

4.1.1 Parameter setting of GTCM

According to the actual operation of Changsha Metro Line 2, the present study sets the parameters in the GTCM as follows.

F_b : The traditional bus fare is 2 RMB, and passengers will enjoy a 30% discount if they use the IC card. Assuming that the passengers using the IC card account for 50% of the total, the traditional bus fare will be 1.7 RMB.

F_r : A mileage-based pricing model is adopted in Changsha Metro, and the price will be 2 RMB if the journey is within 6 km, 3 RMB if from 6 to 11 km, 4 RMB if from 11 to 16 km, 5 RMB if from 16 to 23 km, 6 RMB if from 23 to 30 km, or an additional 1 RMB per increasing 9 km if more than 30 km.

δ : According to international experience, the work utilization coefficient is set to $\delta = 1.0$ when the travel time is within working hours; $\delta = [0.25, 0.75]$ if it is within the free time. The travel situation considered in present study is during the rush hours; thus, $\delta=0.5$.

k : According to the Changsha Statistical Yearbook (2013), the total wages per capita in 2012 is 52,744 RMB. According to 250 business days per year and 8 h per working day, the time value is 26.37 RMB/h.

V_u and V_o : The second ring road is taken for the demarcation line between downtown and suburban areas of Changsha, V_u is assumed to be 15 km/h in downtown, and V_o is assumed to be 25 km/h in suburban.

V_r : The average speed of Metro Line 2 is 36 km/h.

t_1 : Waiting time for bus transfer is 15 min.

t_2 : Waiting time for URT transfer is 5 min.

n_1 : The passengers only transfer once if they go to the CBD (called Wuyi Square) by bus from the downtown area, that is, $n_1 = 1$; they transfer twice if they are from the suburban area, that is, $n_1 = 2$.

n_2 : The present study only considers the accessibility problem of the area near the rail station; thus, passengers only wait once, that is, $n_2 = 1$.

V_w : Some residents often use a free bike rental service and improve the trip efficiency to reach the nearest rail station. The average speed of a bicycle is $V_{w1} = 10$ km/h, and the average speed of the walk is $V_{w2} = 4$ km/h. The chance of riding a bicycle is assumed to be 50%. Hence, $V_w = 7$ km/h.

λ : According to Wang, Sui, and Hu (2010), the comfort coefficient of URT relative to the conventional bus is 1.25.

4.1.2 Results of GTCM analysis

From the above parameters, Table 2 shows the calculated impact range of the URT.

Table 2. Land value-added impact range brought by Changsha Metro Line 2

Serial number	Metro station	S_r (km)	F_r (RMB)	n_1	n_2	C_r (RMB)	R (km)	Station location	
①	West Meixi Lake	10.899	3	2	1	8.591	3.598	Outside the second ring road	
②	Luyun Road	9.713	3	2	1	8.156	3.515		
③	Culture & Arts Center	8.652	3	2	1	7.768	3.449		
④	East Meixihu Lake	7.565	3	2	1	7.369	3.392		
⑤	Wangchengpo	6.488	3	1	1	6.975	2.118	Inside the second ring road	
⑥	Jinxing Road	5.059	2	1	1	5.452	2.100		
⑦	Xihu Park	3.788	2	1	1	4.986	1.751		
⑧	Yingwanzhen	2.513	2	1	1	4.519	1.401		
⑨	Juzizhou	1.375	2	1	1	4.103	1.089		
⑩	Xiangjiang Middle Road	0.697	2	1	1	3.854	0.902		
⑪	Wuyi Square	-	-	-	-	-	0.916		
⑫	Furong Square	0.794	2	1	1	3.890	0.929		
⑬	Yingbin Road	1.493	2	1	1	4.146	1.121		
⑭	Yuanjialing	2.379	2	1	1	4.470	1.364		
⑮	Railway Station	3.416	2	1	1	4.850	1.649		
⑯	Jintai Square	4.088	2	1	1	5.096	1.834		
⑰	Wanjiali Square	5.365	2	2	1	5.564	3.088		Outside the second ring road
⑱	Renmin East Road	6.746	3	2	1	7.070	2.804		
⑲	Changsha Avenue	8.762	3	2	1	7.808	2.948		
⑳	Shawan Park	9.951	3	2	1	8.243	3.043		
㉑	Duhua Road	11.953	4	2	1	9.977	2.872		
㉒	South Railway Station	12.753	4	2	1	10.270	2.942		
㉓	Guangda	14.789	4	2	1	11.015	2.955		

Obviously, a positive correlation exists between the impact range and the distance from the station to CBD. The impact range is also related to fares, speed, transfer mode, transfer wait time, and other factors.

4.2 Measurement of land value-added impact intensity of Changsha Metro Line 2

4.2.1 Data collection and processing

At different areas of the same city in China, although the unit real estate construction costs (mainly including labor cost, material cost, machinery usage fee, etc.) are roughly equal in a short term, the actual market transaction prices of the property undecorated are quite different, this mainly due to the different attached land prices in different geographical locations.

In China, the land ownership belongs to the state, so private individuals or companies can only own or trade land-use rights. In addition, a free land market transaction mechanism has not yet been established, all land management and use right transactions require bidding, auction and listing organized by the Chinese government. Therefore, the data on land management and use right transactions

is scarce, but the transaction data of the property attached on it is relatively sufficient because there is a market-oriented real estate transaction market. Hence, the present study applies property price data instead of land price data.

According to the existing research results (Cervero & Duncan, 2002, Mohammad et al., 2013; Weinstein & Clower, 2002), the value-added impact intensity of residential property is the lowest among different types of properties, so based on a prudential principles of decision-making and the availability of sample data, this study will choose the residential property price data as the samples.

The topographic map and GIS data of the property and other related infrastructure are provided by Changsha Real Estate Management Center. The line map and station GIS data of Changsha Metro Line 2 are provided by China Railway Siyuan Survey and Design Group Co., Ltd. Other relevant data are obtained via the Soufang network, 0731 real estate network, Anjike network, Sohu Focus network, 58 city network, Fang Tianxia network and Sina Leju network. Samples of such data are the residential property price, plot ration, green land ratio, area of the structure, housing age, and so on.

From the above data, obtains two layers by using MapInfo11.0 software: one is the GIS topographic map of the residential property and other related infrastructure of Changsha City, the other is the line map of Changsha Metro Line 2, then superimposes and registers them. According to the different impact ranges on different metro stations, a strip buffer with a width of R (see Table 2) on both sides is generated along the direction of the Changsha Metro Line 2. Figure 3 shows a belt region resembling a dumbbell.

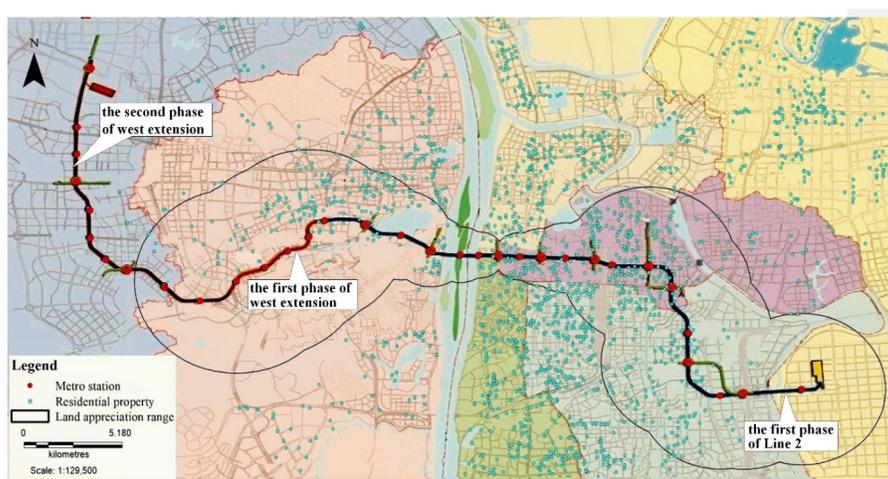


Figure 3. Residential property distribution along Changsha Metro Line 2

As in China's real estate market, instead of being completed by real estate developers in accordance with certain standards, most residential properties are decorated individually by the owners according to their personal habits and economic conditions, so in the transaction of second-hand residential properties, the prices are not only affected by their locations, but also by the degree of their decoration. Obviously, If only consider the impact of different location characteristics on residential property prices, then it is unfit for using the second-hand residential properties with different decoration degrees as the research samples.

Based on the above actual market conditions, the research only chooses the ordinary residential property without decoration as the research object, and 389 effective samples are selected from the striped buffer. Moreover, the average transaction prices of residential property in July 2014 are adopted to avoid the changes in other systemic factors in different time points. Distances from residential prop-

erty to the nearest URT stations and CBD are derived from the MapInfo11.0 system. Tables S1 and S2 show all the sample data (see the Supplementary Data File).

4.2.2 Results of spatial econometric model analysis

A spatial correlation test of data should be conducted before the spatial model is built. Moran's I is the most common method used to test the overall spatial effect; Moran's $I \in [-1, 1]$; a greater $|I|$ means a higher correlation.

A logarithmic process is performed for the price data of 389 residential properties and a global correlation analysis is conducted using GeoDa0.95i software. Figure 4 shows that Moran's I is 0.3687.

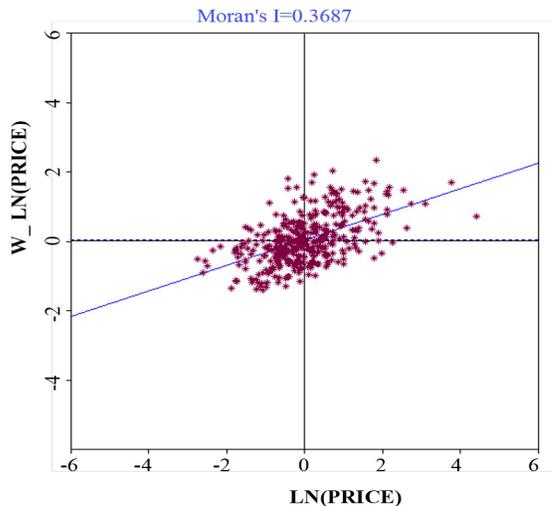


Figure 4. Moran index scatter plot of the residential property prices

Obviously, $I > 0$, the prices of property have a positive spatial correlation. Hence, the results obtained from ordinary least square (OLS) model may be biased. Therefore, using a spatial econometric model for analysis is advised.

OLS estimation is conducted first, and the results show that the value of F-statistic is 20.1357, and the Prob. (F-statistic) is $7.29686e-036$. Hence, the model is significant, and the data in this research is effective.

A comparative analysis of the regression results of OLS, SLM, and SEM is conducted by using GeoDa0.95i. Figure 3 shows that the samples are dense and sufficient in downtown but scattered and insufficient in the suburb. Hence, the determination of the weight in SLM and SEM is based on adjacency relationship. The K-nearest neighbors method is chosen, and the number of neighbors is set to 4. Table 3 shows the comparative results.

Table 3. Regression result comparison of OLS, SLM, and SEM

Dependent variable	OLS	SLM	SEM
R-squared:	0.4111	0.4466	0.4467
Akaike info criterion:	-268.9500	-285.5690	-287.2410
Scharz criterion:	-213.4600	-226.1150	-231.7511
Log likelihood:	148.4750	157.7850	157.8206

The R-squared in SLM and SEM is better than in OSL. Moreover, the AIC and SC values in SLM and SEM are smaller, and the values of Log-likelihood are greater than OSL. This result means that the fitting goodness of spatial model is superior to traditional HPM. SEM provides a better estimation than SLM; thus, SEM will be selected in further research.

Regression analysis is made with SEM. Table 4 shows the results.

Table 4. SEM estimation of residential property prices within 3.6 km

Variable	Coefficient	Std. Error	z-value	Probability	VIF
<i>Constant</i>	8.8455	0.0743	119.0540	0.0000	–
<i>DS</i>	-0.0499	0.0142	-3.5087	0.0005	1.161
<i>DCBD</i>	-0.04	0.0054	-7.4703	0.0000	1.654
<i>Bus</i>	0.0068	0.0017	3.9690	0.0001	1.178
<i>PSMS</i>	0.0269	0.0182	0.9269	0.3540	1.093
<i>PW</i>	0.0228	0.0188	1.2174	0.2235	1.028
<i>Market</i>	0.0597	0.0210	2.8400	0.0045	1.066
<i>Hospital</i>	0.0164	0.0185	0.8867	0.3753	1.027
<i>GLR</i>	0.3462	0.1004	3.4499	0.0006	1.229
<i>PR</i>	-0.0100	0.0057	1.7408	0.0817	1.255
<i>Age</i>	-0.0108	0.0024	-4.5465	0.0000	1.030
<i>AS</i>	0.0006	0.0003	2.0887	0.0367	1.088
<i>BS</i>	0.0293	0.0174	1.6818	0.0926	1.071
<i>Floor</i>	-0.0188	0.0287	-0.6556	0.5121	1.118
LAMBDA	0.2104	0.0636	3.3073	0.0009	-

Judging by the VIF, the model has no multiple collinearities, indicating that the regression model is effective. The significance test results of each variable are shown as follows: *DS*, *DCBD*, *Bus*, *Market*, *GLR*, and *Age* pass 1%; *AS* passes 5%; *PR* and *BS* pass 10%, and symbols of all these regression coefficients conform with expectation; however, *PSMS*, *PW*, *Hospital*, and *Floor*, fail to pass the significance level test of 10%.

According to the results estimated above, within 3.6 km from the metro station, the residential property price averagely increases by 4.99% as it is 1 km closer to the metro station.

The impact range is subdivided into three intervals to investigate further on whether the impacts on residential property prices present a tiered change. The intervals are 0–1, 1–2, and 2–3.6 km, and the number of samples are 190, 145, and 54, respectively. Estimations are made by SLM and SEM. After comparison, SEM estimations of three sections are all superior to SLM estimations. Hence, SEM analysis results continue to be taken for regression coefficients of relevant variables. Table 5 shows the results.

Table 5. SEM estimation of residential property prices of each interval

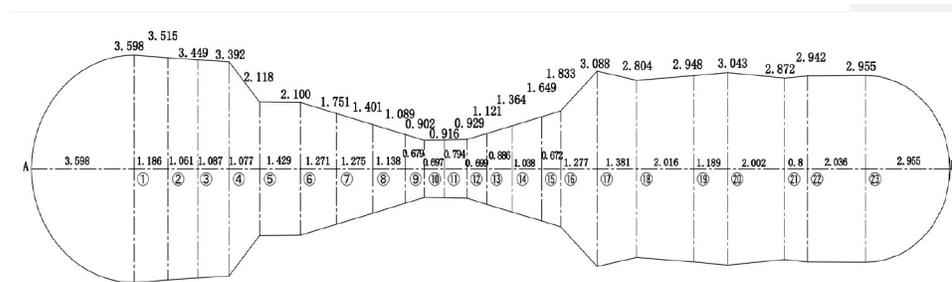
Variable	Regression coefficient		
	0–1 km	1–2 km	2–3.6 km
<i>DS</i>	-0.1473***	-0.0479***	-0.0183***
<i>DCBD</i>	-0.0460***	-0.0302***	-0.0368***
<i>Bus</i>	0.0059***	0.0085***	0.0072***
<i>PSMS</i>	0.0469	0.0264	0.0234
<i>PW</i>	0.0394	0.0236	0.0196*
<i>Market</i>	0.0795***	0.0431***	0.0573**
<i>Hospital</i>	0.0210	0.0351*	0.0144
<i>GLR</i>	0.3418***	0.4468***	0.0284***
<i>PR</i>	-0.0096*	-0.0095*	-0.0108**
<i>Age</i>	-0.0159***	-0.0115***	-0.0094***
<i>AS</i>	0.0008**	0.0006**	0.0006*
<i>BS</i>	0.0391*	0.0288*	0.0272**
<i>Floor</i>	-0.0240	-0.0250	-0.0184

Note: ***, **, and * indicate the variable passes through the significance level test on 1%, 5%, and 10%, respectively.

If the residential property is close to the metro station, then, its price increases by 14.73% within the range of 0–1 km, by 4.79% within 1–2 km, and by 1.83% within 2–3.6 km. The price increment decreases if far from the metro station, presenting a tiered decreasing pattern. This result is consistent with the research conclusion of Shenzhen Metro (Gu & Zheng, 2010), but the impact magnitude is relatively less. The possible reason is that the operation time of Changsha Metro Line 2 is short, and a hysteretic characteristic about the land value-added impact exists.

4.3 Benefit measurement of land increment along Changsha Metro Line 2

On the basis of prudential principles of decision-making, the area within 0–1 km is defined as S_1 , and the mean of corresponding value-added intensity is $\bar{f}(S_1) = 0.0976$. Similarly, the area within 1–2 km is defined as S_2 and $\bar{f}(S_2) = 0.0331$; the area within 2–3.6 km is defined as S_3 and $\bar{f}(S_3) = 0.00915$. All the curves connecting the adjacent farthest impacted points are changed to straight lines to simplify the calculation. Figure 5 shows that a value-added impact area including a series of trapezoidal connections forms in the middle and two semicircles on each end.



Note: The station names represented by ①, ②, ..., ⑳ are the same with Table 2

Figure 5. Area diagram of the land value-added along Changsha Metro Line 2

According to the above three intervals of 0-1 km, 1-2 km and 2-3.6 km, calculates the area of land value-added impact area, as shown in Table 6.

Table 6. Calculation of the land value-added impact area along Changsha Metro line 2

Station (including the farthest point of impact)	Lateral distance (km)	Longitudinal distance (km)	Affected area S_1 (million sq.m)	Affected area S_2 (million sq.m)	Affected area S_3 (million sq.m)
A (the farthest point outside of West Meixi Lake)	0	3.598	7.053	6.446	6.830
West Meixi Lake	3.598	1.186	2.372	2.372	3.692
Luyun Road	3.515	1.061	2.122	2.122	3.232
Culture and Arts Center	3.449	1.087	2.174	2.174	3.087
East Meixihu Lake	3.392	1.077	2.153	2.153	1.625
Wangchengpo	2.118	1.429	2.858	2.858	0.311
Jinxing Road	2.100	1.271	2.542	1.910	0.318
Xihu Park	1.751	1.275	2.550	1.469	0.000
Yingwanzhen	1.401	1.138	2.276	0.557	0.000
Juzizhou	1.089	0.679	1.225	0.126	0.000
Xiangjiang Middle Road	0.902	0.697	1.114	0.000	0.000
Wuyi Square	0.697	0.794	1.291	0.000	0.000
Furong Square	0.929	0.699	1.299	0.134	0.000
Yingbin Road	1.121	0.886	1.771	0.430	0.000
Yuanjialing	1.364	1.038	2.075	1.051	0.000
Railway Station	1.649	0.672	1.344	0.996	0.000
Jintai Square	1.834	1.277	2.554	2.128	1.602
Wanjiali Square	3.088	1.381	2.762	2.762	2.613
Renmin East Road	2.804	2.016	4.032	4.032	3.533
Changsha Avenue	2.948	1.189	2.378	2.378	3.759
Shawan Park	3.043	2.002	4.004	4.004	3.833
Duhua Road	2.872	0.800	1.600	1.600	1.451
South Railway Station	2.942	2.036	4.072	4.072	3.861
Guangda	2.955	2.955	5.735	4.956	3.024
B (the farthest point outside of Guangda)	0				
Total			63.356	50.731	42.769

In the “Classification of Urban Land and Standard of Land for Planning and Construction” (Chinese GB50137-2011) and “Changsha City Master Plan (2003-2020),” it is supposed that the plots within 3.6 km away from the URT stations are urban construction land including residential land, commercial service facility land, industrial land, transportation facility land, public management and public service land, logistics and storage land, public facility land, green space plaza, etc. Among them, residential land accounts for 32%, commercial and service facility land accounts for 4%, and the sum is 36%.

The average exchange rate of USD against RMB in 2014 is 6.1428. According to the relevant statistical data and results calculated above, Table 7 shows the value-added benefits of various divided areas.

Table 7. Land value-added benefit brought by Changsha Metro 2

	Area S_1	Area S_2	Area S_3
Land area (million sq.m)	63.356	50.731	42.769
Proportion of land use	0.36	0.36	0.36
Plot ratio	3.7815	3.0693	3.3381
Area of structure (million sq.m)	86.2491	56.0540	51.3962
Average price of housing (\$/m ²)	1,153.871	1,033.568	995.3116
Intensity of value-added	0.0976	0.0331	0.00915
Land value-added of unit area (\$/m ²)	112.6178	34.2111	9.1071
Value-added benefits (billion USD)	9.7132	1.9177	0.4681

Therefore, the total land value-added benefit from Changsha Metro Line 2 in July 2014 is

$$Y = \sum_{j=1}^n V_j = 9.7132 + 1.9177 + 0.4681 = 12.099 \text{ billion USD.}$$

4.4 Land area for integrated development along Changsha Metro Line 2

Following-up the previous study (Tang, Cui, Zhang, & Chen, 2019), the study still takes Changsha Metro Line 2 as the case, if set the calculation base period to be 2009, the discount rate is calculated to be 1.0558 by the Capital Asset Pricing Model, and the investment benefits of Changsha Metro Line 2 from 2009 to 2043 is $Y_t = -124.13$ million USD, the project investment loss will be 162.85 million USD if it is discounted to 2014 at the discount rate of 1.0558. The 60% loss is compensated via integrated land development, that is, $\tau = 0.6$, and the amount of government subsidies is 97.71 million USD. If all the land used for integrated development is within the area S_1 , the returned proportion Ψ is 50%, then land area for integrated development is $A_d = 97.71 / (112.6178 \times 0.5) = 1.7353$ million sq.m.

4.5 Special land tax of Changsha Metro Line 2

From the actual situation of the Chinese market, the value-added income of the undeveloped land along the URT line will flow directly into the government's finances after the auction transaction. Hence, its value capture is not considered here.

Changsha Metro Line 2 is taken as an example, and the special land tax of property in developed areas is calculated. The taxation rate is set to 30% for commercial and office property and 10% for residential property to reflect certain social welfare. On the basis of Eq. (12), the amount of special urban land tax is calculated as $\text{Tax} = 12.099 \times [(0.32 / 0.36) \times 0.1 + (0.04 / 0.36) \times 0.3] = 1.48$ billion USD.

5 Conclusion

URT plays a positive role in promoting the land value along the line. Based on the test and verification of the spatial effect in the real estate market, the present study constructs the GTCM to measure land value-added impact range from URT, the SLM and the SEM to measure land value-added impact intensity, and the models to estimate and capture the benefit of land value-added. Then, taking Changsha Metro Line 2 as an example, the land value-added benefit brought by URT is quantitatively evaluated.

The entire land value-added impact range of Changsha Metro Line 2 resembles a dumbbell, that is, the impact range of the stations near the CBD is relatively smaller, as the distance from the CBD gradually increases, the range of value-added impact appears to increase. The spatial correlation test shows that the prices of property along the URT line have a positive spatial correlation, further study results are that the fitting goodness of spatial model is superior to traditional HPM, and SEM provides a better estimation than SLM. The impact intensity decreases when it is far from the metro station, thereby presenting a tiered decreasing pattern. Other conclusions are that the land value-added benefit from Changsha Metro Line 2 reached 12.099 billion USD, the land area for integrated development is 1.7353 million sq.m, and the special urban land tax from the property in developed areas is 1.48 billion USD.

The empirical results show that the land value-added benefit occupies a large share of the external benefits. Hence, in order to solve the problem of fund shortage during URT project construction and operation, the primary task of internalizing is to successfully return it to URT corporation, thus some policy suggestions should be put forward for the integrated land development and special land tax. From the operability level, integrated development is the most direct and possible method to capture the land value-added benefit. The government should reasonably determine the allocation area of the land for integrated development and the proportion of land appreciation benefit returned to URT corporation. As for the land with a different development extent, different integrated development strategies are proposed as follows.

As for the mature development areas (including the old town), land-use density is at a high level. Hence, it should be developed with the consideration of line direction and the location of URT entrances and exits. Priority should be given to adjust the land-use mode, then transform the old town and URT to an organic whole in the adjacent area of stations. This process will provide convenience for passengers' direct entry to nearby office buildings, large shopping malls, hotels, banks, pharmacies, entertainment venues, and other destinations. It will also create a three-dimensional urban landscape and modern shopping and leisure corridors.

The construction area is in a large-scale construction period, its land-use density is not high, the city functions still need to be improved, and it has a certain room for development. The integrated development in this region should increase the intensity of land development based on the further improvement of planning and design. Furthermore, private investors should be encouraged to participate in the joint development through capital share mode.

As for the planning area, traffic-oriented development (TOD) mode is recommended, that is, using the land allocated by the government, builds numerous compact and function-mixed TOD communities within a certain range (especially 1 km). Residential, retail, office, and other public resources are grouped together. Residents can easily complete a trip task by walking or using a combination of URT, traditional public transport, and bicycles. Obviously, TOD mode consciously guides residents to use URT to meet their travel demand. It can not only increase the passenger flow of URT, but also improve the land development and utilization efficiency and achieve a multi-win-win situation among the government, passengers, rail transit companies and real estate developers.

The state owns the land in China, and property tax currently remains in the exploration stage. The land value-added benefit can be partially returned to the government through two types of taxes, namely, land value-added and urban land-use tax, then the government will return it to the URT corporation in the form of subsidies. For the fully developed land along the line, the government can formulate relevant tax policies and hierarchically collect special land tax from the existing property based on the results calculated above. The government must also establish a corresponding mechanism to coordinate interests and reasonably assign this special revenue tax as the construction and operation subsidies to URT corporation, then further promote the sustainable development of URT.

Through quantitatively analyzing the spatial effect of land appreciation from URT, this study builds a basic framework for internalizing the external benefits of URT project, then provides a basis for project decisions of investors and government. However, several limitations of this study should be acknowledged.

URT project goes through different stages, such as planning, designing, construction, initial operation and mature operation, and it may have different effects on land value at various stages (Mohammad, 2013). Limited to the length of the article, the present study only selects the sample data in July 2014 as the research object. Moreover, the residential property is only selected as the research object, while the business, office and other types of property are excluded, so compared with the actual land value-added benefit brought from URT, the results of this study may be underestimated. The subsequent studies can incorporate other property types to compare residential property, as well as to make further longitudinal comparison and analysis of the land value-added impact in different periods by using panel data. Although this study has explained the advantages of the method of GTCM theoretically when calculating the impact range of land appreciation, it has not been compared with the actual market price data, so following-up studies can make a comparative analysis by using big data analysis technology and verify the superiority of the GTCM in further. Since there is no express bus in Changsha yet, this study does not consider its impact and only makes a comparison of conventional buses and URT, so adding express buses to determine a more accurate land value-added impact range of URT is also worthy of further research when applying this method to the study of other cities.

Acknowledgements

The present study is supported by the National Social Science Foundation of China (14BGL160), Natural Science Foundation of Hunan Province (2016JJ4011), Open Foundation of Innovation Platform of Hunan Colleges and Universities (17K008), Enterprise Strategic Management and Investment Decision Research Base of Hunan Province (19qyzd02).

References

- Atkinson-Palombo, C. (2010). Comparing the capitalization benefits of light-rail transit and overlay zoning for single-family houses and condos by neighborhood type in metropolitan Phoenix, Arizona. *Urban Studies*, 47(11), 2409–2426.
- Cervero R., & Duncan, M. (2002). Transit's value-added effects: Light and commuter rail services and commercial land value. *Transportation Research Record*, 1805, 8–15.
- Chu, N., Jiang, B., Li, X., & Luo, C. (2016). Generalized transportation costs and land value increment along Harbin-Dalian high-speed railway. *Journal of Transportation Systems Engineering and Information Technology*, 16(2), 19–24.
- Clower, T. L., & Weinstein, B. L. (2002). The impact of Dallas (Texas) area rapid transit light rail stations on taxable property valuations. *Australasian Journal of Regional Studies*, 8, 389–400.
- Cohen, J. P., & Brown, M. (2017). Does a new rail rapid transit line announcement affect various commercial property prices differently? *Regional Science and Urban Economics*, 66, 74–90.
- Du, H., & Mulley, C. (2012). Understanding spatial variations in the impact of accessibility on land value using geographically weighted regression. *Journal of Transport and Land Use*, 5(2), 46–59.
- Gibbons, S., & Machin, S. (2005). Valuing rail access using transport innovations. *Journal of Urban Economics*, 57, 148–169.
- Golub, A., Guhathakurta, S., & Sollapuram, B. (2012). Spatial and temporal capitalization effects of light rail in phoenix from conception, planning, and construction to operation. *Journal of Planning Education and Research*, 32(4), 415–429.
- Gu, Y., & Zheng, S. (2010). The impacts of rail transit on property values and land development intensity: The case of No.13 Line in Beijing. *Acta Geographica Sinica*, 65(2), 213–223.
- Guo W., Zhang, Y., You, J., Hu, J., & Pei, X. (2016). Travel modal choice analysis for traffic corridors based on decision-theoretic approaches. *Journal of Center South University*, 23, 3028–3039.
- Hess, D. B., & Almeida, T. M. (2007). Impact of proximity to light rail rapid transit on station-area property values in Buffalo, New York. *Urban Studies*, 44(5–6), 1041–1068.
- Hui, E. C., Ho, V. S., & Ho, D. K. (2004). Land value capture mechanisms in Hong Kong and Singapore: A comparative analysis. *Journal of Property Investment & Finance*, 22, 76–100.
- Ibeas, Á., Cordera, R., Dell'Olio, L., Coppola, P., & Dominguez, A. (2012). Modelling transport and real-estate values interactions in urban systems. *Journal of Transport Geography*, 24, 370–382.
- Kim, J., & Zhang, M. (2005). Determining transit's impact on Seoul commercial land values: An application of spatial econometrics. *International Real Estate Review*, 8(1), 1–26.
- Knaap, G., Ding, C., & Hopkins, L. (2001). Do plans matter? The effects of light rail plans on land values in station areas. *Journal of Planning Education and Research*, 21(1), 32–39.
- Litman, T. (2007). Evaluating rail transit benefits: A comment. *Transport Policy*, 14, 94–97.
- Macfarlane, G. S., Garrow, L. A., & Moreno-Cruz, J. (2015). Do Atlanta residents value MARTA? Selecting an autoregressive model to recover willingness to pay. *Transportation Research Part A: Policy and Practice*, 78, 214–230.
- McMillen, D. P., & McDonald, J. (2004). Reaction of house prices to a new rapid transit line: Chicago's Midway line, 1983–1999. *Real Estate Economics*, 32(3), 463–486.
- Mohammad, S., Graham, D., Melo, P., & Anderson, R. (2013). A meta-analysis of the impact of rail projects on land and property values. *Transportation Research Part A: Policy and Practice*, 50, 158–170.
- Pan, Q. (2013). The impacts of an urban light rail system on residential property values: A case study of the Houston METRO rail transit line. *Transportation Planning and Technology*, 36(2), 145–169.
- Pagliara, F., & Papa, E. (2011). Urban rail systems investments: An analysis of the impacts on property

- values and residents' location. *Journal of Transport Geography*, 19, 200–211.
- Pior, M. Y., & Shimizu, E. (2001). GIS-aided evaluation system for infrastructure improvements: Focusing on simple hedonic and Rosen's two-step approaches. *Computers, Environment and Urban Systems*, 25(2), 223–246.
- Seo, K., Golub, A., & Kuby, M. (2014). Combined impacts of highways and light rail transit on residential property values: A spatial hedonic price model for Phoenix, Arizona. *Journal of Transport Geography*, 41, 53–62.
- Su, Y., & Feng, C. (2011). An analysis on influences to the residential price of real estate brought by urban railway system: A case study of Beijing MTR 4th Line and Batongxian. *Urban Development Studies*, 18(7), 108–113.
- Tang, W., Cui, Q., Zhang, F., & Chen, Y. (2019). Urban rail-transit project investment benefits based on compound real options and trapezoid fuzzy numbers. *Journal of Construction Engineering and Management*, 145(1), 05018016.
- Wang, S., Sui, D., & Hu, B. (2010). Forecasting technology of national-wide civil aviation traffic. *Journal of Transportation Systems Engineering and Information Technology*, 10(6), 95–102.
- Wang, Y., Feng, S., Deng, Z., & Cheng, S. (2016). Transit premium and rent segmentation: A spatial quantile hedonic analysis of Shanghai Metro. *Transport Policy*, 51, 61–69.
- Weinstein, B. L., & Clower, T. L. (2002). *An assessment of the DARTLRT on taxable property valuation and transit oriented development*. Denton, TX: Center for Economic Development and Research, University of North Texas.
- Wen, H., Zhang, Z., & Zhang, L. (2011). An empirical analysis on spatial effects of the housing price based on spatial econometric models: Evidence from Hangzhou City. *Systems Engineering-Theory & Practice*, 31(9), 1661–1667.
- Xu, T., Zhang, M., & Aditjandra, P. T. (2016). The impact of urban rail transit on commercial property value: New evidence from Wuhan, China. *Transportation Research Part A: Policy and Practice*, 91, 223–235.
- Yan, S., Delmelle, E., & Duncan, M. (2012). The impact of a new light rail system on single-family property values in Charlotte, North Carolina. *Journal of Transport and Land Use*, 5(2), 60–67.
- Yang, J., Quan, J., Yan, B., & He, C. (2016). Urban rail investment and transit-oriented development in Beijing: Can it reach a higher potential. *Transportation Research Part A: Policy and Practice*, 89, 140–150.
- Yang, L., & Shao, C. (2008). Integrated forecasting model for real estate price along urban rail transit based on BP neural network and Markov chain. *Journal of Jilin University (Engineering and Technology Edition)*, 38(3), 514–518.
- Zhang, M., & Xu, T. (2017). Uncovering the potential for value capture from rail transit services. *Journal of Urban Planning and Development*, 143(3), 04017006.
- Zhang, M., & Wang, L. (2013). The impacts of mass transit on land development in China: The case of Beijing. *Research in Transportation Economics*, 40(1), 124–133.
- Zhong, H., & Li, W. (2016). Rail transit investment and property values: An old tale retold. *Transport Policy*, 51, 33–48.