

Article

Walking Accessibility to the Bus Stop: Does It Affect Residential Rents? The Case of Jinan, China

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Abstract: It is a crucial question to understand the relationship between public transit and residential rents for the proposal of a sustainable transportation system and efficient allocation of lands during the policy marking process. Little has been discovered in the current literature regarding the impact of the bus system on residential rents. This study investigated walking accessibility to the bus stop based on the average daily on-ridership data of bus stops and street networks in Jinan, China, and analysed the impact on the spatial differentiation of residential rents using the spatial autocorrelation analysis and the geographically weighted regression (GWR) method. Our results suggested that residential rent levels in Jinan had evident spatial dependence and spatial differentiation characteristics, which was signified by a significant high rent, and a high accessibility distribution pattern surrounding both city and sub-city centres. GWR results further showed that walking accessibility to the bus stop could significantly improve residential rents. On the spatial scale, a 1% increase in walking accessibility could result in a premium of up to 0.427% and a 2.984% decline in rental prices. Lastly, we found that walking accessibility to the bus stop significantly affected housing rents incrementally with increasing distance between residences and the city centre. Moreover, walking accessibility to the bus stop showed a marginal ‘first increase and then decrease’ effect on residential rents as the distance to the bus stop increased. The premium effect was the most significant among residences within 500–900 m of a bus stop.

Keywords: walking accessibility to the bus stop; hedonic price model; residential rent; geographically weighted regression



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1. Introduction

With the development of continuously accelerating urbanisation in China, the influx of people in cities has generated a massive demand in the urban housing rental market. As a result, rental housing plays an important role in solving housing problems for the low-income and floating population [1]. To ease the supply–demand imbalance and deal with the high rent growth rate in the rental market, the Chinese government has adopted a series of housing policies to improve this market’s operating mechanism. For example, the government increased the proportion of rental housing and enforced equal rights for rental and sale [2]. According to the land rent theory and the location equilibrium theory of urban economics, the choice of housing rental location is the result of a trade-off between the rental price and commuting cost under the condition of certain income, in order to meet the maximisation of utility [3]. In reality, the development of urban public transport facilities has not only introduced changes to modern commuting methods with lower costs but also reshaped the spatial pattern of urban housing rental prices. The Ministry

of Natural Resources released the spatial planning guide for the community life unit in July 2021. This guide suggests that the government further play the role of a platform for community life circle and improve the convenience of residents' access to public service facilities within a certain walking distance/time for the benefit of people's wellbeing [4]. Therefore, optimising the spatial allocation of public transport facilities and improving the walking accessibility to public transport facilities have become an urgent matter to promote the coordinated development of public transport and the housing rental market.

Accessibility is an important index to evaluate the fairness of public services, which is defined as potential opportunities for interaction [5]. The accessibility of public transit facilities is a key indicator of the degree of transportation convenience, measuring the accessibility of public transport facilities [6]. Most studies on housing and rental prices used the distance to the public transit, the cumulative–opportunity method and the gravity index model to measure the transit accessibility [6–8]. Literature suggests that the straight-line distance and the network distance are popular measurements of the distance to the public transport station [7]. However, the distance to the transit measurement can be problematic, since it cannot reflect the relationship between supply and demand and the impact of other transit stations on residents [9]. The cumulative–opportunity method could count the number of accessible transit stations within a specified travel time or distance [10]; however, it assumed that these public transit stations have the same impact on the residents, regardless of the distance to the residence. The gravity index model is closely related to the cumulative–opportunity method and could discount the attractiveness of opportunities based on their distances [10,11]. It also considers the demand feature (on/off ridership) of the facilities [8]. As one of the key factors in accessibility calculations, travel distance/time in the gravity index model is usually measured by the origin–destination (OD) distance along the road network, which can reflect the actual range of residents' travel more accurately [8,9].

To examine the impact of transit accessibility on urban residential rental prices, current research usually adopted the hedonic price model in empirical analysis. The hedonic price model originated from Lancaster's new consumer theory and Rosen's empirical analysis method [12,13]. The rent of a house is the function of its inherent features, and to some extent, the rent reflects consumers' demands and preferences for different attributes, including housing attributes, public service amenities attributes, public transportation attributes, and location attributes [1,14]. Regarding the approaches to modelling housing and rental prices in the literature, apart from the standard ordinary least squares (OLS) method, spatial econometric models (such as the spatial lag model and spatial error model), accounting for the spatial dependence of housing and rental prices, were also applied widely to empirical research [15,16]. However, current models could not reveal the spatially varying parameters of the independent variables, which is a response to the heterogeneity of the real estate market [17]. Thus, geographically weighted regression (GWR) was widely adopted in many studies [18,19].

Among the different public transit systems, rail transit and bus rapid transit (BRT) has been the focus of current studies, and most of them showed that there was a positive relationship between these two transportation methods and housing and rental prices [19,20]. In contrast, there was little evidence of the impact of bus transit on rental prices [20,21]. Studies suggest that bus transit had a positive impact on housing prices, which also showed spatial heterogeneity [15,22,23]. Research has also investigated spatial impact scope and discussed the varieties in the impact of public transport on land value, with the change of residential location and distance from public transit [8,20]. Most studies have proved that rail transit stations in suburban areas have a greater impact on urban housing rental prices than in urban centres [16,20]. With the change of distance from rail transit stations, residential rents or housing prices also vary. Benjamin et al. [24] found that there was a negative correlation between the distance from the apartment to the subway station and the rental price. For every 100-m increase in the distance to the subway station, the rental price decreased by 2.5%. Du and Mulley [25] showed that rail transit stations have a signif-

ificant impact on housing prices within 500 m. Jun et al. [26] suggested that the influence range of the subway station in Seoul is 600 m on the neighbourhood scale. However, the transit accessibility method, characterised by either straight line distance or shortest path distances to public transit (or both), ignores the quality characteristics of public transport services. This made the spatial influence range of public transport on housing prices or rental prices deviate.

To summarize, although the impact of transit accessibility on residential rental prices has been well documented, there are still some underdeveloped gaps in the literature. First, existing studies have measured transit accessibility based on the assumption of homogenisation of each public transit station, ignoring the various traffic demands as well as the street configuration. Therefore, it is impossible to comprehensively reveal the convenience of transit in travel. Second, few studies [14,15,18,19] have revealed the spatial differentiation and spatial influence range of transit accessibility on residential rent levels; therefore, they could not fully reveal the mechanism thereof. Lastly, current studies have mainly focused on the ‘accessibility to rail transit’ measure in large cities. However, as of December 2020, only 43 cities in China have rail transit systems [27]. This suggests that the majority of cities in China rely heavily on bus transportation compared to rail transit systems. Therefore, for most bus-served cities in China, research on the impact of accessibility to the bus stop on residential rents requires more attention [28].

To further explore how public transit service facilities affect the residential rents, we adopted the gravity index model to examine the walking accessibility to the bus stop in Jinan, which is the capital city in Shandong Province, China. We also used spatial autocorrelation and the GWR method to evaluate the spatial performance of bus transit. Our results revealed the mechanism of action under heterogeneous residential locations and the neighbourhood conditions where the bus stops are located. This study has implications for future developments of public transportation and efficient use of lands in Jinan and other cities which rely heavily on public transport systems.

2. Data and Methods

2.1. Data

2.1.1. Study Area

As a central city of the downstream Yellow River, Jinan is currently going through a rapidly urbanisation process, which is a reflection of major cities in China. Our study is conducted primarily in the central area of Jinan (Figure 1), which is located east of the Yufu River, west of the east ring line of the expressway, south of the Yellow River, and north of the mountain area [29]. This area encompasses five administrative regions, namely, the Huaiyin District, the Licheng District, the Lixia District, the Shizhong District, and the Tianqiao District. The entire study area is 337 km² and has a population of 2.82 million people, which accounted for 77.3% of the urban population of Jinan. Jinan has a relatively mature bus network system [30]. By the end of 2020, there were 340 bus lines, more than 5800 buses in operation, and an average of more than 2 million passengers on daily basis. Jinan also has 13 BRT lines, four trolleybus lines, and three rail transit lines [31]. According to the residents’ travel survey report in 2019, 24.88% of residents rely on public transport for travel¹.

2.1.2. Data Source

The basic research data in this study is the unit rent of a single house (listed for rent) obtained from the ‘Lianjia’ (<http://www.lianjia.com> (accessed on 3 September 2021)) platform using the web scraping technique. The data were collected in September 2021. After excluding commercial and office buildings, shared houses, and villas, the final sample consists of 13,211 units to be rented. The geographic location information of the residential samples was obtained by the AutoNavi platform. Administrative divisions, urban public transit network datasets, and Point of Interest (POI) data are sourced from Shandong Provincial Geographic Information Public Service Platform (<http://www.sdmap.gov.cn/>

[index.html](#) (accessed on 5 September 2021)). The passenger ridership data of bus stops in 2021 is obtained from the Integrated Circuit (IC) card data of the Jinan Municipal Transportation Bureau.

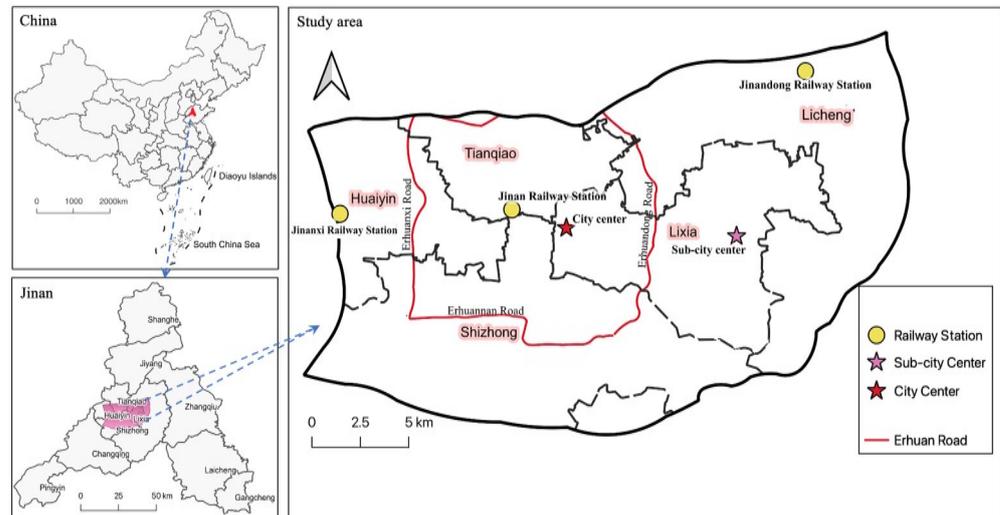


Figure 1. Map of Study area in Jinan.

2.1.3. Indicator System

The traditional hedonic price model considers the housing price to be the sum of the implicit price of the inherent attributes of the house, which usually includes three aspects: building attributes, neighbourhood attributes, and location attributes. Many empirical studies on residential rents are also based on these attributes [32–34]. However, there are differences in residents' preferences for buying and renting houses, and the latter often highlights the attributes of convenience, including the convenience of transportation, employment, schooling, business services, public services, and leisure and recreation [20]. Therefore, this study relied on the theoretical model of hedonic rent constructed by related research [1,14,20], adopted the 'quartile' element framework, and divided the attributes of residential rents into location attributes, neighbourhood attributes, housing attributes, and transportation attributes. Table 1 describes the subdivision variables of these four attributes and corresponding analysis methods. Location attributes represent the centrality of the residence, measured by accessibility to the city centre and sub-centre from the residence [35]; neighbourhood attributes reflect the public service facilities adjacent to the residence, including living facilities, medical facilities, education facilities, and leisure facilities, etc.; housing attributes includes the housing size, age, the decoration condition, and the number of the floors, etc.; according to the research goal, transportation attributes are measured by walking accessibility to the bus stop and other transportation attributes (i.e., proximity to bus lines, proximity to a rail station, and proximity to a subway station) [35–40].

Table 1. Indicator system of influencing factors of residential rents.

Attribute Classification	Explanatory Variables	Description	Analysis Method
Location attributes	Accessibility to the city centre Accessibility to the sub-city centre	Time taken to get to the city centre by bus Time taken to get to the sub-city centre by bus	Directions application program interface (API) in AutoNavi
Neighbourhood attributes	Distance to a shopping centre Distance to a tertiary hospital Distance to primary and secondary schools Distance to a park	The shortest distance to a nearby shopping centre, including large supermarkets, shopping malls, shopping centres The shortest distance to a tertiary hospital The shortest distance to primary and secondary schools The shortest distance to a park	Nearest neighbour analysis in Arcgis
Housing attributes	Number of floors Number of toilets Housing size Well-decorated Housing age	Discrete variable Discrete variable Discrete variable Dummy variable (Yes = 1, No = 0) Discrete variable	Web crawl from Lianjia.com (accessed on 3 September 2021)
Transportation attributes	Walking accessibility to bus stop Proximity to a railway station Proximity to a subway station Proximity to bus lines	The number of bus stops within a network radius of 900 m from the residence, considering distance impedance and passenger weight (daily average ridership of bus stops) Dummy variable (whether it is located within 2000 m of the railway station, including Jinan Station, Jinandong Station, and Jinanxi Station) Dummy variable (whether it is located within 1000 m of the subway station) Dummy variable (whether it is within 400 m of the bus line)	Urban Network Analysis (UNA) Nearest neighbour analysis in Arcgis

2.2. Methods

2.2.1. Evaluation of the Walking Accessibility to the Bus Stop

This study used the Urban Network Analysis (UNA) toolkit to measure walking accessibility to the bus stop along the street network. The UNA tool has two main advantages in characterising resident travel. Firstly, it uses the distance of the road network as the standard, which reflects the actual range of residents' travel more realistically and can also capture the spatial configuration along the street network to bus stops. Secondly, it adopts the analysis idea of 'network + node' to the road as a network concept, wherein buildings and public facilities as nodes, and can also assign corresponding weights to nodes. Here, we used the gravity index model from the UNA Toolbox [8,41] and weighted bus stops with ridership data to measure accurately the walking accessibility of travel from each residence to bus stops accurately. The gravity index model is expressed as follows:

$$Gravity^r[i] = \sum_{j \in G - \{i\}, d[i,j] \leq r} \frac{W[j]^\alpha}{e^{\beta \cdot d[i,j]}} \quad (1)$$

In Formula (1), i is the residence (departure); j represents the bus stop (destination); G is the road network; r represents the shortest network radius, we set it as 900 m, which is about a 15-min trip for residents to walk; $d[i, j]$ represents the shortest network distance between the starting point i and the destination j ; the weight $W[j]$ represents the average daily on-ridership at bus stop j ; α is a parameter to adjust the weight; and β is a parameter to adjust the distance decay. According to the criteria proposed by Sevtsuk and Kalvo [42], we set α and β to be 0.5 and 0.001, respectively. Finally, a higher gravity index value implies better accessibility.

2.2.2. OLS and GWR Model

OLS method is one of the most popular statistical techniques used in traditional regression models. It could express the relationships between the dependent variable and the explanatory variables, being possible also to identify the strength of the relationships between them [35]. However, it was not ideal when dealing with spatial non-stationary data regression estimation. In contrast, GWR model allows us to capture spatially varying relationships between dependent and independent variables in a spatially decomposed manner, rather than treating them as spatially constant [43]. Based on the hedonic rent model, to capture spatially varying relationships between the residential price and independent variables, the GWR model is expressed as follows:

$$P_i = \beta_0(u_i, v_i) + \sum_{j=1}^k \beta_j(u_i, v_i)x_{ij} + \varepsilon_i \quad (2)$$

In Formula (2), P_i represents the rents of the i -th house, x_{ij} represents the value of the i -th house, the j -th explanatory variable, (u_i, v_i) represents the coordinates of the i -th house; $\beta_j(u_i, v_i)$ represents the regression coefficient of the i -th house, and the j -th the explanatory variable, while ε_i represents the random error.

3. Results

3.1. Spatial Pattern and Spatial Correlation Analysis of Residential Rents

We calculated the average monthly rent for each residential house to reveal the spatial pattern of residential rents. The results showed great spatial differences in residential rental prices in Jinan, with an average rent of 30.25 yuan/(m²·month) and a maximum rent of 115.38 yuan/(m²·month), mainly distributed in the range of 20–40 yuan/(m²·month) (accounting for 62.42% of the total number of houses). Based on the spatial correlation analysis of GeoDa, the global Moran's I value was 0.211 at the significance of 0.01, indicating a spatial dependence of residential rents [44]. As shown in Figure 2, the residential rents present a spatial 'east high and west low, south high and north low' distribution pattern.

Taking Jingshi Road as the axis, the rent levels show an ‘increasing first and then decreasing’ trend from west to east. Residential rent levels located between the city centre and the sub-city centre are significantly higher than those of other areas, and high-rent residential buildings are mainly concentrated near the city centre.

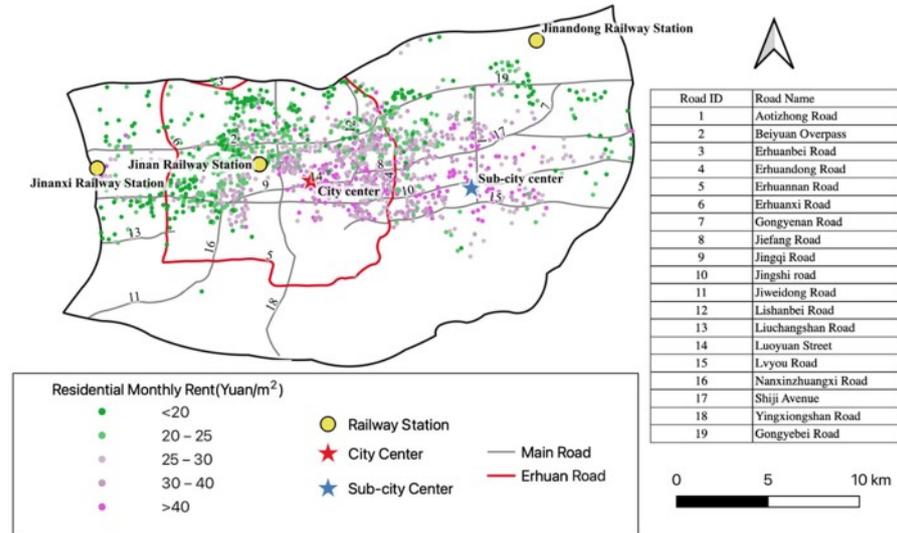
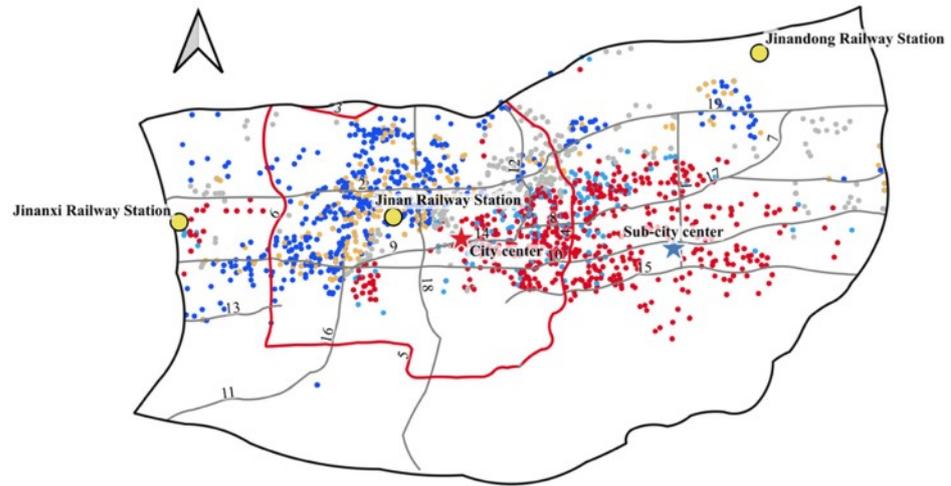


Figure 2. The spatial distribution pattern of residential rent levels in the main urban area of Jinan.

We further explored the spatial local agglomeration characteristics of residential rents. As shown in Figure 3A, taking the city centre as the dividing point, the agglomeration of residential rental space in Jinan is divided into two main areas: (1) the southeast region, which presents a ‘high–high’ agglomeration distribution, and (2) the northwest region, which presents a ‘low–low’ agglomeration distribution, with evident spatial autocorrelation.



(A)

Figure 3. Cont.

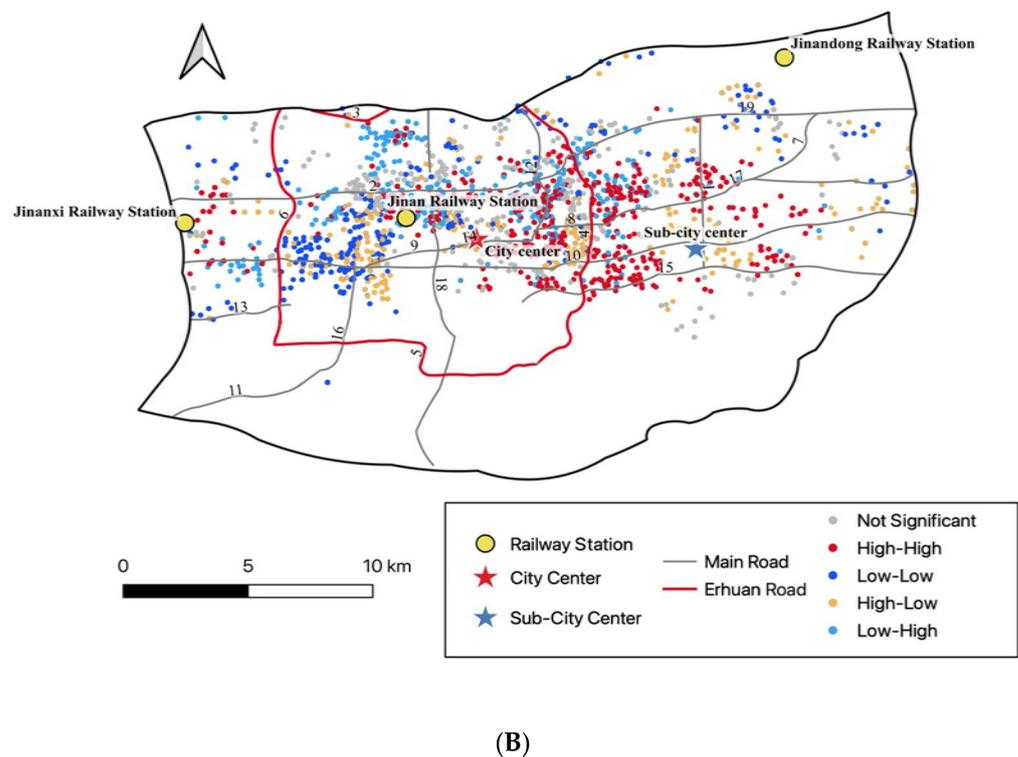


Figure 3. Local autocorrelation characteristics of residential rents (A). Local autocorrelation characteristics between residential rents and walking accessibility (B).

Moreover, we used bivariate spatial local autocorrelation analysis to explore the spatial correlation between residential rents and walking accessibility to the bus stop. As shown in Figure 3B, the residential areas between the city centre and the sub-city centre mainly show a ‘high rent, high accessibility’ (high–high) type of agglomeration, indicating that the urban development of Jinan is showing a ‘dual city centre’ and ‘dual traffic centre’ spatial correlation pattern. This verifies the traditional land tax theory in urban economics [3]—that is, the rent premium in the city centre is complementary to the transportation cost savings. The ‘low rent, low accessibility’ (low–low) type is mainly distributed in the area between Erhuanxi Road and Nanxin Zhuangxi Road. The ‘high rent, low accessibility’ (high–low) and ‘low rent, high accessibility’ (low–high) distributions are more scattered. However, it can still be seen that in the main urban area of Jinan, ‘high rent, low accessibility’ (high–low) residences are more distributed in the southeast, while ‘low rent, high accessibility’ (low–high) residences are more distributed in the northwest. This means that for the northwest of Jinan’s main urban area, the high walking accessibility to the bus stop cannot lead to a high rental market: for the southeast of Jinan’s main urban area, low walking accessibility to the bus stop is closely correlated with high rent, as there exists spatial mismatch in the area.

3.2. The Effect of Walking Accessibility to the Bus Stop on Residential Rents

3.2.1. OLS Model Results

We performed global regression analysis using a multivariable linear regression model in the form of a log–log function, where dummy variables (proximity to bus lines, proximity to a railway station, proximity to a subway station, and well-decorated) and discrete variables were not converted to natural logarithmic form. Analysing the results of OLS model estimation in Table 2, it can be found that R^2 is 0.4693, and the p value of the F test is less than 0.001, indicating that the results are reliable. Moreover, the variance inflation factors (VIF) of the explanatory variables are less than 7.5, meaning that there are no multicollinearity problems in the regression [45]. The results show that: (1) the coefficient of the ‘walking accessibility’ is 0.0239 at the 0.01 significance level. This result indicates that a 1% increase in walking accessibility could increase average rent by 0.0239%. (2) The

'accessibility to city centre' and 'accessibility to sub-city centre' variables also significantly affect residential rents, but sub-city centre accessibility has a more significant impact on residential rents. The coefficient of the 'accessibility to the sub-city centre' is -0.228 , showing that for every 1% increase in the travel time of public transportation to the sub-city centre, the residential rents decrease by 0.228%. (3) The 'proximity to bus lines' variable has a significant positive effect on residential rents; it reflects the important impact of adjacent transit on residents' travel, which is inconsistent with the results of research on residential prices, such as Mulley et al. [46] and Yang et al. [35], who proved that the adjacent BRT corridor has a negative price effect on residential prices. This inconsistency reflects the difference in preference between renters and homebuyers for houses adjacent to bus lines. Buyers pay more attention to the environmental attributes of houses, while renters care more about the traffic conditions of houses. (4) The 'proximity to a subway station' variable fails to increase the residential rents, displaying that the subway construction in Jinan does not play a positive role in increasing the residential rents. This is because Jinan has relatively fewer subway lines and its subway stations are mostly located in suburbs. Although in the central area with high rental demand, due to the lack of relevant subway supporting facilities, the premium effect of the 'proximity to a subway stations' variable on rent cannot be identified.

Table 2. OLS model estimates.

Variable	Coefficient	t Value	Standardized Coefficient	VIF
Walking accessibility to the bus stop	0.0239 ***	9.91	0.0685	1.15
Proximity to a subway station	-0.101 ***	-12.96	-0.0863	1.07
Proximity to bus lines	0.0288 ***	4.17	0.0282	1.11
Accessibility to the city centre	-0.0212 **	-1.95	-0.0135	1.17
Accessibility to the sub-city centre	-0.2280 ***	-20.92	-0.1498	1.24
Well-decorated	0.2677 ***	44.34	0.2876	1.02
Housing size	0.5364 ***	67.78	0.5435	1.56
Number of toilets	0.1053 ***	13.58	0.1079	1.53
Distance to a park	-0.0427 ***	-9.09	-0.0610	1.09
Distance to primary and secondary schools	-0.0348 ***	-8.71	-0.0625	1.24
Distance to a tertiary hospital	-0.0853 ***	-22.36	-0.1635	1.29
Constant	8.226 ***	74.12	-	-
R^2	0.4693			
F(11, 12843)	946.24			
Prob(F-statistic)	<0.0001			
AIC	8632.78			

Note: ***, ** indicate that the p value is significant at the 1%, 5% levels, respectively. Only variables with significant effects are shown in the table.

Among other influencing factors, housing attributes are the most significant factors in residential rents. For every 1% increase in residential areas, the average rent increases by 0.5364%. On average, the rent of a well-decorated residence is 30.70% higher than that of a less decorated residence². Secondly, with respect to the neighbourhood attributes, accessibility to parks, primary and secondary schools, and tertiary hospitals all have a significant impact on residential rents.

3.2.2. GWR Model Results

Although the OLS regression model can analyse the direction and magnitude of the average impact of related variables on residential rents, it insufficiently estimates the spatial variations of these variables [47]. Through the GWR model, we obtained the local regression results of the factors affecting residential rents (Table 3). In the model, the spatial weights were determined by an adaptive Gaussian kernel function, and the optimal kernel bandwidth was determined by minimising the Akaike Information Criterion (AIC). Table 3 reveals that the average impact direction of most variables in the GWR model is consistent

with the impact direction of the OLS model, which confirms the robustness of the regression results. Nevertheless, compared with the OLS model, the GWR model has a better fit, with an R^2 value of 0.762 and an AIC value of 4951.43, making it a better mode. Specifically, the effects of all the variables on rent vary greatly at the spatial scale. Among them, the average influence coefficient of walking accessibility to the bus stop on residential rents is 0.013. On the spatial scale, a 1% increase in walking accessibility can result in a premium of up to 0.427% and may also lead to a decline in rental prices to 2.984%. It can be seen that OLS regression cannot capture the spatial impact of variables and underestimates the real impact. On average, every 1% increase in public transport travel time to the city centre will lead to a reduction of up to 2.736% in residential rents. Furthermore, somewhere within 400 m of a bus line, the rent premium reaches a maximum of 38.8%.

Table 3. GWR model estimates.

Variable	Mean	Minimum	Median	Maximum
Walking accessibility to the bus stop	0.013	−2.984	0.022	0.427
Accessibility to the city centre	−0.147	−2.736	−0.087	0.906
Proximity to bus lines	0.031	−0.528	0.037	0.328
Proximity to a subway station	−0.106	−1.775	−0.043	2.582
Well-decorated	0.17	−0.078	0.171	0.342
Number of toilets	0.151	−0.118	0.126	0.52
Housing size	0.699	−0.325	0.736	1.304
Distance to a tertiary hospital	0.13	−0.997	0.072	1.348
Distance to a shopping mall	−0.041	−0.473	−0.047	0.25
Distance to primary and secondary schools	−0.053	−0.477	−0.037	0.314
Distance to a park	−0.131	−1.078	−0.105	0.201
Constant	0.114	−1.846	0.223	2.615
R^2	0.762			
AIC	4951.43			

To analyse the spatial heterogeneity impact of transportation factors more intuitively, we mapped the local coefficients of key variables by inverse distance weighted (IDW) interpolation. Figure 4 shows the local coefficients of transportation variables such as walking accessibility to the bus stop, proximity to a subway station, and proximity to bus lines. As shown in Figure 4A, there is a significant spatial difference in the impact of ‘walking accessibility to the bus stop’ on residential rents. Specifically, the impact is highest around the sub-city centre and the eastern part of the main urban area. However, in the area between Jinan Station and the city centre and the area at the junction of Erhuanxi Road and Erhuanbei Road, there is no positive impact. This may be because the development of the bus system in this part of the region is relatively complete, resulting in a decline in residents’ willingness to pay for housing. As shown in Figure 4B, in most areas along the subway lines, ‘proximity to a subway station’ has a positive premium effect on residential rents, such as in areas near Jinanxi Railway Station and the sub-city centre, where subway proximity raises residential rents. In contrast, no premium effect on subway station proximity on rentals is identified in areas lacking subway facility support, such as the southern part of the old city centre and the eastern part of the main city. As shown in Figure 4C, most of the areas in the main urban area of Jinan show a premium effect of bus line proximity on residential rents, indicating that renters highly value the residential transit proximity feature. The positive effect of ‘proximity to bus lines’ on residential rents is most significant in areas such as Jinanxi Railway Station, City Centre, and Aotizhong Road; while in areas such as the northern part of Jinan Station and the vicinity of the sub-city centre, ‘proximity to bus lines’ has a significant negative effect on residential rents, which is due to the fact that rail transit has been built in these areas, making it difficult for the advantages of the bus system to be exerted. Conversely, ‘proximity to bus lines’ may lead to negative externalities such as traffic congestion and environmental pollution, which in turn have a negative impact on residential rents.

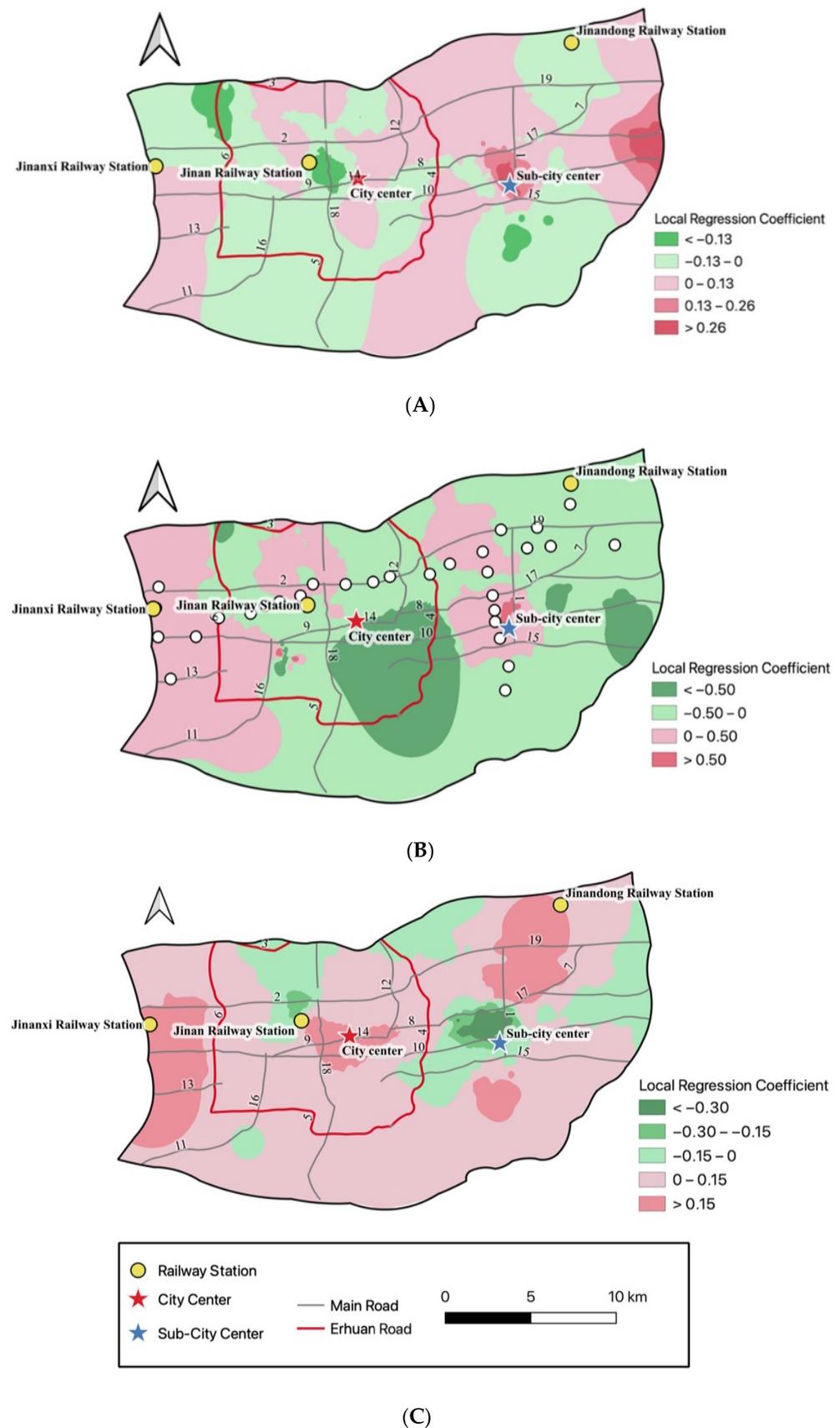


Figure 4. Local coefficients of the ‘walking accessibility to the bus stop’ variable (A). Local coefficients of the ‘proximity to a subway station’ variable (B). Local coefficients of the ‘proximity to bus lines’ variable (C).

3.2.3. Heterogeneity Analysis

To reveal the impact mechanism of walking accessibility to the bus stop on rents under spatial heterogeneity, we analysed the impact mechanism from the perspectives of heterogeneous residential locations and bus stop neighbourhood conditions. The results are shown in Tables 4 and 5, respectively.

Table 4. OLS regression results of residential location heterogeneity.

Variable	Coefficient	t Value	VIF
Walking accessibility to the bus stop	0.0181 ***	7.46	4.48
Proximity to a subway station	−0.1033 ***	−13.79	1.07
Proximity to bus lines	0.0154 **	2.30	1.12
Accessibility to the sub-city centre	−0.2671 ***	−26.95	1.11
Located within 2 km of the city centre	0.1161 ***	5.25	1.67
Located 5–10 km away from the city centre	−0.2133 ***	−19.87	3.13
Located more than 10 km from the city centre	−0.1849 ***	−14.67	4.76
Located within 2 km of the city centre × Walking accessibility to the bus stop	0.0608 ***	4.82	1.60
Located 5–10 km away from the city centre × Walking accessibility to the bus stop	0.0528 ***	8.98	3.38
Located more than 10 km from the city centre × Walking accessibility to the bus stop	0.0863 ***	14.69	3.06
Well-decorated	0.2556 ***	43.81	1.03
Housing size	0.5378 ***	70.08	1.58
Number of toilets	0.1080 ***	14.44	1.53
Distance to a park	−0.0307 ***	−6.72	1.12
Distance to primary and secondary schools	−0.0283 ***	−7.07	1.35
Distance to a tertiary hospital	−0.0641 ***	−13.38	2.20
Constant	8.1292 ***	79.67	-
R ²	0.5072		
F(16, 12,865)	778.83		
Prob(F-statistic)	<0.0001		
AIC	7696.95		

Note: ***, ** indicate that the *p* value is significant at the 1%, 5% levels, respectively. Only significant variables are shown in the table.

Table 5. OLS regression results of bus stop neighbourhood scale.

Variable	Distances to the Bus Stop (m)				
	d ≤ 200	200 < d ≤ 500	500 < d ≤ 900	900 < d ≤ 1500	1500 < d ≤ 2000
Walking accessibility to the bus stop	−0.0184 (−0.76)	0.0292 (1.93)	0.0703 *** (4.36)	0.0680 *** (4.69)	0.025 (1.69)
Accessibility to the city centre	0.00264 (0.12)	0.0489 (1.86)	−0.282 *** (−7.90)	−0.200 *** (−7.34)	−0.184 *** (−5.95)
Well-decorated	0.328 *** (13.38)	0.211 *** (9.97)	0.374 *** (19.23)	0.295 *** (15.21)	0.0472 (1.01)
Housing size	0.327 *** (13.4)	0.346 *** (16.21)	0.283 *** (19.5)	0.215 *** (10.35)	−0.160 *** (−6.78)
Number of toilets	0.155 *** (5.04)	0.286 *** (10.59)	0.347 *** (14.63)	0.360 *** (15.2)	0.469 *** (9.64)
Distance to a park	−0.0497 (−1.93)	−0.159 *** (−8.95)	−0.0494 *** (−3.78)	0.0214 (1.41)	−0.0435 (−1.60)
Distance to primary and secondary schools	−0.0822 *** (−3.86)	−0.0089 (−0.55)	−0.0610 *** (−4.87)	−0.0524 *** (−4.14)	−0.0829 * (−2.56)
Distance to a tertiary hospital	0.0199 (1.21)	0.0163 (1.18)	0.0692 *** (5.28)	−0.010 (−0.70)	−0.114 * (−2.49)
Constant	6.704 *** (25.51)	6.393 *** (26.64)	8.182 *** (27.2)	4.643 *** (21.38)	7.881 *** (16.78)

Note: ***, * indicate that the *p* value is significant at the 1%, 10% levels, respectively.

Heterogeneity Analysis of Residential Location

Table 4 shows that a change of residential location has a significant impact on rents. Taking 2–5 km from the city centre as a reference standard, rents for residences located within 2 km of the city centre are 18.61% higher³, while rents for residences located 5–10 km and 10 km or more from the city centre are 15.43% and 12.51% lower, respectively. According to the interaction effect, the walking accessibility to the bus stop at residences located 10 km away from the city centre has the highest influence coefficient on residential rents (for every 1% increase in walking accessibility, residential rents increase by 0.0863%). This shows that poorly located residences are more reliant on buses and that the advantages of traffic conditions can make up for the residential location disadvantage to a certain extent. Conversely, in residences with a better location, due to their proximity to the city centre, employment opportunities and rents are relatively higher, although the perfect transit infrastructure and dense bus lines network result in relatively high walking accessibility to the bus stop. The effect of walking accessibility to the bus stop on the rents will be relatively smaller. Thus, urban planning departments should strengthen the construction of public transit infrastructure in outer suburbs to meet the travel needs of citizens better.

Heterogeneity Analysis of Bus Stop Neighbourhood Scale

To explore the heterogeneous neighbourhood scale of a bus stop, we divided the network distance between residences and bus stops into five categories—within 200 m, 200–500 m, 500–900 m, 900–1500 m, and 1500–2000 m—and calculated the corresponding walking accessibility to the bus stop, setting the network distance as 200 m, 500 m, 900 m, 1500 m and 2000 m, respectively. We then ran the OLS regression. The results are shown in Table 5. It could be seen that with the increase of the distance to the bus stop, the marginal effect of the walking accessibility to the bus stop on the residential rents shows the trend of ‘first increase and then decrease’. When the residence is within 200 m of the bus, the impact of the walking accessibility to the bus stop on the residential rents is insignificant and negative. This is because residences adjacent to the bus stop are more sensitive to negative traffic factors such as noise and air pollution. However, when the residence is 200–1500 m away from the bus stop, the impact of walking accessibility becomes positive as the distance increases. However, it has the most significant premium effect on rent levels in residences within 500–900 m of a bus stop, with a coefficient of 0.0703. When the distance to the bus stop exceeds 900 m, the impact of the walking accessibility gradually decreases. Once the residence is 1500–2000 m away from the bus stop, the impact is insignificant.

4. Discussion

4.1. Scientificity and Accuracy of Walking Accessibility to the Bus Stop

The measure of transit accessibility has always been a talking point. Most studies utilise radius distance or straight line distance to depict travel convenience as the proxy of transit accessibility [6,7]. However, compared with straight line distance, network distance can better reflect the travel behaviour of residents [8,48]. In addition, high-quality public transit nodes are often accompanied by high travel demand. Most of the existing studies ignored the variety in travel demand of heterogeneous traffic nodes and considered them the same weights on the spatial scale, which resulted in measurement bias [49,50]. To close this gap and scientifically reflect the objective supply and subjective demand of public transit facilities in the evaluation, this study used the gravity index model from the UNA toolbox to measure the walking accessibility to the bus stop accurately based on street network distance as well as the daily average on-ridership data to weight bus stops.

4.2. The Effect of the Walking Accessibility to the Bus Stop on Residential Rents

This study provides empirical evidence of a large city in China to help explain the relationship between the accessibility of the bus stop and residential location selection, which is of great significance to promote the sustainable development of public transit and land use for Jinan and other large cities. Both OLS and GWR results show that walking

accessibility to the bus stop has a significant effect on the rental market, which implies that the government should prioritise pedestrian-friendly street layouts in the housing supply. Thus, in urban planning, streets should be carefully configured and more frequent and interconnected short streets should be built [51]. This conclusion is congruent with the research of Seoul by Kang et al. [8].

Specifically, the GWR results show that for those living near a bus stop with high passenger flow, walking accessibility to the bus stop tends to have a higher impact on residential rents. However, the impact of the subway on residential rents has certain limits in space; proximity to subways only has a premium effect on residential rents for those living in areas near subway stations. Additionally, in areas with dense bus lines, adjacent bus lines cannot promote residential rent premiums because of negative externalities such as traffic congestion and environmental pollution. This conclusion is consistent with that of Cao et al. [52], who found that adjacent bus lines had a negative impact on the rental market in small cities due to the nuisance effect of buses.

Furthermore, although numerous studies have proved that public transit had a spatial impact on land value [14,53,54], few studies clearly explained the spatial impact scope considering heterogeneous residential locations and bus stop neighbourhood scale. In this regard, this study further reveals that areas far from the city centre are more dependent on bus transportation. In contrast, in areas with a better location, due to more travel options, the effect of walking accessibility to the bus stop on rents is trivial, conforming to the law of ‘diminishing marginal effect’ of willingness to pay for rents. This conclusion is consistent with Gu et al. [55], who demonstrated that rail transit stations have a greater impact on suburban housing prices than in downtown areas. Therefore, the urban planning department should pay more attention to the needs of residents in areas located far from the city centre, strengthen the construction of public transit infrastructure in the outer suburbs, and provide more convenient transportation services. Moreover, for areas with better location conditions and higher walking accessibility to the bus stop, the supply of rental housing should be increased correspondingly.

Additionally, as the distance to the bus stops increases, the marginal effect of the impact of walking accessibility to the bus stop on residential rents shows conformity to the law of ‘first increase and then decrease’. Specifically, walking accessibility has the most significant premium effect on residences 500–900 m from the bus stop. In contrast, for residences located within 200 m of public transit facilities, high walking accessibility can restrain residential rents. This result proves that adjacent bus stops are more susceptible to the nuisance effect of bus travel, such as traffic congestion and environmental pollution, causing renters to avoid bus stops to a certain extent.

4.3. Limitations

There are a number of limitations to this study. First, similar to most previous studies, the effects found in this study are more of an association than a causality because the data are cross-sectional, thus failing to reflect the temporal changes in effects. Secondly, due to data availability issues, the rent data used in this study is listing price data rather than transaction price data. Although the two are often highly correlated, the results may be slightly biased. This could be improved for a more in-depth analysis. Nevertheless, the research framework we designed in this study is innovative and can guide further studies. Furthermore, it could be helpful in promoting the coordination of public transportation and land use planning for large cities in China.

5. Conclusions

In this study, we measured walking accessibility to the bus stop based on the distance of residential street networks and average daily on-ridership at bus stops, which integrated the supply and demand of public transit facilities. By adopting spatial autocorrelation analysis and the GWR method, we estimated the effect of walking accessibility to the bus

stop on residential rents under the background of forming a 15-min community life circle in Jinan. Our findings are as follows:

- (1) Residential rent levels in Jinan show evident spatial dependence and spatial heterogeneity. The bivariate local autocorrelation results indicate that in the Jinan city centre and sub-city centre, both residential rent levels and walking accessibility to the bus stop reflect a ‘high-high correlation’ distribution, showing a pattern of coupling and correlation between ‘dual city centre’ and ‘dual traffic centre’. In contrast, ‘high rent, low accessibility (high–low)’ residences are mostly distributed in the south-eastern part of the city, while ‘low rent, high accessibility (low–high)’ residences are mostly distributed in the north-western part of the city.
- (2) GWR results show that walking accessibility to the bus stop could significantly improve residential rent levels. On the spatial scale, a 1% increase in walking accessibility could result in a premium of up to 0.427% and may also lead to a decline in rental prices to 2.984%. However, a residence’s proximity to a subway does not necessarily lead to higher rent. Further, residential rent levels increase in most areas close to bus lines. However, due to negative externalities such as traffic congestion and environmental pollution, the nuisance effect generated by this proximity will also reduce the premium effect of renting.
- (3) The results of the heterogeneity analysis show that as the distance between a residential area and the city centre increases, the impact of walking accessibility to the bus stop on rental prices increases. Specifically, it has a higher impact on residential rent levels in the outer suburbs, while having little impact on the rent in residences closer to the city centre, conforming to the law of ‘diminishing marginal effect’ of willingness to rent. Besides, with the increase of the distance to the bus stop, the marginal effect of the walking accessibility to the bus stop on the residential rents shows the trend of ‘first increase and then decrease’. Moreover, it has the most significant premium effect in residences within 500–900 m of a bus stop.

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Notes

¹ This report “Jinan Residents Travel Survey Report” is published by Jinan Urban and Rural Transportation Bureau in 2019.

² The hedonic rent model formula is $\ln Y = aX + bM + A + v$, where X represents other control variables, M is the dummy variable of well-decorated residences, A is the constant, and v is the error. Therefore, for a well-decorated residence, $\ln Y_1 = aX + b + A + v$, for a less decorated residence, $\ln Y_2 = aX + A + v$, and the rental premium of a well-decorated residence over that of a less decorated residence is $Y_1/Y_2 - 1 = e^{\ln Y_1 - \ln Y_2} - 1 = e^b - 1$.

³ The hedonic rent model formula is $\ln Y = aX' + bM_1 + cM_2 + dM_3 + fM_1 \ln X + gM_2 \ln X + kM_3 \ln X + A + v$, where M is a dummy variable for the distance to the city centre, such that M_1 means within 2km from the city centre, M_2 means 5–10 km away from the city centre, and M_3 means more than 10 km away from the city. $\ln X$ represents walking accessibility (take the mean value. $\ln X = 0.8973$, if $M_1 = 1, M_2 = 0, M_3 = 0$; $\ln X = 0.8653$, if $M_1 = 0, M_2 = 1, M_3 = 0$; $\ln X = 0.5928$, if $M_1 = 0, M_2 = 0, M_3 = 1$). X' is other

control variable. Therefore, for residences within 2 km of the city centre, $\ln Y_1 = aX' + b + \ln X + A + v$, for residences within 2–5 km from the city centre, $\ln Y_2 = aX' + A + v$, and the rental premium of residences within 2 km over that of those within 2–5 km is $Y_1/Y_2 - 1 = e^{\ln Y_1 - \ln Y_2} - 1 = e^{b + \ln X} - 1$.

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