



Identifying the Spatial Heterogeneity in the Effects of the Social Environment on Housing Rents in Guangzhou, China

Yang Wang^{1,2} · Kangmin Wu^{1,2} · Lixia Jin^{1,2} · Gengzhi Huang³ · Yuling Zhang¹ · Yongxian Su^{1,2} · Hong'ou Zhang¹ · Jing Qin^{4,5}

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Abstract

Housing rents in cities is an important topic in the study of urban geography and an area that needs to be focused on to develop livable cities. As a critical component of the urban environment, the social environment influences housing rents and should not be neglected. However, little research examines how spatial heterogeneity in the social environment impacts housing rents. To address this gap, this paper performs a case study of Guangzhou, China and constructs a livability-oriented social environment conceptual framework that covers five aspects: educational background, occupation, unemployment, floating population, and rental household. It then develops datasets of the influencing factors such as the social environment as well as the building, convenience, physical environment, and location characteristics for 1,328 communities in Guangzhou. Ordinary least squares (OLS) and mixed geographically weighted regression (mixed GWR) model are then employed for further analyses. The results show that the mixed GWR model is more effective than the OLS and classical GWR models. Four aspects of the social environment—educational background, occupation, floating population, and rental household—have a spatially heterogeneous relationship with housing rents. The impact of the social environment on housing rents is more evident in suburban districts. The current findings help to better understand the spatial limitation of the social environment's impact on housing rents, which enables policy makers to develop evidence-based, spatially differentiated affordable rental housing programs and provides theoretical support for the development of livable cities.

Keywords Mixed geographically weighted regression model · Guangzhou · Social environment · Housing rents · Spatial heterogeneity

✉ Kangmin Wu
kangmwu@163.com

Extended author information available on the last page of the article

Introduction

Approximately 1.2 billion people rely on rental housing to meet their housing needs (Gilbert, 2016). Over the past two decades, demand for rental housing has grown rapidly because of urbanization (Cui et al., 2018). The rental market has become an indispensable segment of the housing market, and renting has become an important way of life for residents in China's megacities. In Beijing, Shanghai, Guangzhou, and Shenzhen, rental households account for 33.58%, 32.75%, 40.58%, and 72.68% of all households, respectively (1% Population Survey, 2015, Urban Areas Section), indicating the existence of a "renting era" in megacities. Rent is a core indicator of the housing market; therefore, the housing rents in megacities should be studied. Analyzing the key elements that constitute housing rents is key to understanding the mechanism through which housing rents are determined and provides evidence for developing policies targeting the rental housing market. Therefore, the influencing factors of housing rents are a core topic of the research on rental markets.

Rents vary significantly based on the types of housing in a city (Nishi et al., 2019) due to the housing type characteristics (Zhang et al., 2019). The hedonic price model offers a useful perspective for analyzing the factors that affect housing rents. According to this theory, the characteristics of housing units are the only factors that influence housing rents. Existing research indicates these influencing factors can be sorted into the following categories: (1) building characteristics (Leung & Yiu, 2019) such as the gross area, age, facilities, interior design, quality of finishes, and seismic standards (Cao et al., 2019; Gan et al., 2016; Leung & Yiu, 2019; Nakagawa et al., 2007); (2) convenience characteristics such as access and proximity to public transit (especially rail transit) (Cui et al., 2018; Efthymiou & Antoniou, 2013), roads (D'Arcangelo & Percoco, 2015), employment centers (Cui et al., 2018), public facilities (Kuroda, 2018; Li et al., 2019), shopping centers (Zhang et al., 2019), and arts and entertainment centers (Haurin & Brasington, 1996); and (3) physical environmental characteristics, such as green space (Jun & Kim, 2017) and noise (Efthymiou & Antoniou, 2013; Zambrano-Monserrate & Alejandra Ruano, 2019). Among the location characteristics, the distance to the central business district (CBD) is a frequently used measure (Muhammad, 2017).

Much of the existing research on the environmental characteristics has focused on the physical environment, while little research has been dedicated to the study of the social environment. In fact, the social environment is an important part of the urban environment and a critical determinant in the residents' choice of housing location (Jiang et al., 2017). A few works have examined the impact of the factors that constitute the social environment on housing rents. For instance, McCord et al., find that housing rents are influenced by social and political conflicts as well as territory segregation based on race and religion (McCord et al., 2014). Therefore, these factors have impacts on housing rents that should not be ignored.

The social attributes of human beings (e.g., occupation, income, educational level, social status, cultural attributes, and race) define the social environment. People with different social attributes tend to live in different areas, thereby creating spatial variation in the social environment. Both the Marxist and structuralist

schools maintain that the social environment is an important dimension in residents' housing decisions; these decisions affect and define the social environment (D, 1973; Cassel & Mendelsohn, 1985). The social environment not only determines the characteristics of housing supply but also influences residents' locational choice of rental housing, thereby affecting the rent level. For an area with a relatively inferior social environment, satisfaction with the neighborhood is usually low (Basolo & Yerena, 2017), and potential renters tend to avoid such areas. As a result, the rents are generally low.

Within a given city, housing rents show apparent spatial heterogeneity (Kuroda, 2018; Zhang et al., 2019). To measure the impact of spatial heterogeneity on housing rents, the local regression method (e.g., geographically weighted regression) has been employed to analyze the factors that influence housing rents (Agudelo Torres et al., 2015; Tomal, 2020). Therefore, the impact of the social environment on housing rents may not apply to the entire region. Thus, when residents make decisions that are influenced by the locations of rental properties, the social environment may be only one factor for consideration in certain communities and may not have any material effect in other communities. This phenomenon leads to spatial heterogeneity in the social environment's impact on housing rents.

Guangzhou is an economically developed, first-tier city. Rental households account for 40.58% of all households in the city; this ratio is high in comparison to that in the rest of the country. Across the city, the housing characteristics are apparently spatially heterogeneous (Jim & Chen, 2006; Wang et al., 2020), and the social environment in Guangzhou is complex and diverse (Han & Wu, 2020; Li et al., 2020; Zhou et al., 2015), making it a good fit for a case study.

Therefore, this work examines spatial heterogeneity in the relationship between the social environment and housing rents. Specifically, taking Guangzhou as the case for study, we identify communities in which the social environment has a significant impact on the housing rents as well as those where no such significant impact exists. Furthermore, we examine the direction and strength of the impact of the social environment, where it exists, on the housing rents and the characteristics of the impact's spatial heterogeneity.

To study these issues, we construct cross-sectional datasets that cover the housing rents, five factors of the social environment, and eight other influencing factors for 1,328 communities in Guangzhou, China. In a global analysis of the social environment's impact on the housing rents across this city, we apply a mixed geographically weighted regression model to explore spatial heterogeneity in the extent and direction of the social environment's impact on the housing rents across Guangzhou's 1,328 communities. Unlike previous research, this study focuses on spatial heterogeneity in the social environment's impact on housing rents. The findings will improve our understanding of the spatial limitation of the social environment's impact on housing rents and spatial heterogeneity in terms of the impacts of different social environmental indicators on housing rents. This work will help city administrators develop spatially differentiated rental market policies and affordable rental housing programs, thereby increasing the city's livability, attractiveness, and competitiveness.

The rest of the paper proceeds as follows. Section 2 discusses the social environment as a concept and our research design, indicators, data, and research methods. Section 3 analyzes our research findings regarding spatial heterogeneity in the social environment and housing rents in Guangzhou, the extent and direction of the social environment's global impact on housing rent distributions, and the spatial heterogeneity of this impact. Section 4 discusses the research findings and draws conclusions.

Concept, Research Design, and Methods

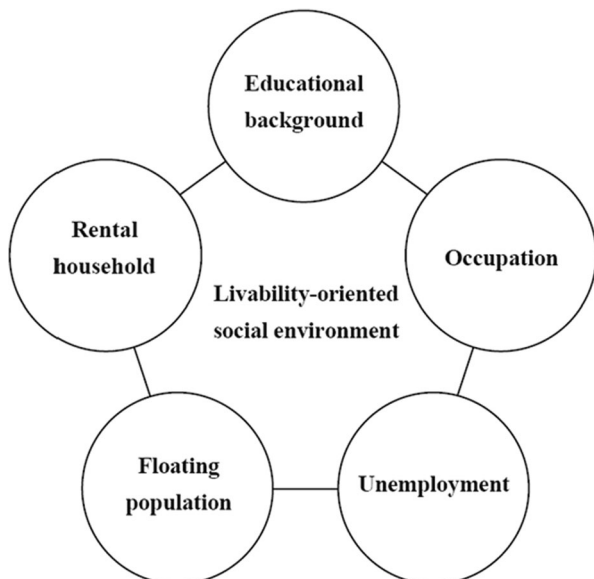
Livability-Oriented Social Environment

The conceptual framework of the social environment has multiple facets and varies with study contexts. We propose a conceptual framework of a livability-oriented social environment from a housing rent perspective. The framework covers five aspects: educational background, occupation, unemployment, floating population, and rental household (Fig. 1).

The five aspects and their indicators are detailed as follows:

- 1) Educational background (denoted by the proportion of highly educated people in the population; PHEP). People with a bachelor's degree or above are defined as highly educated. The percentage of highly educated people among those aged six and above is the indicator of a community's educational background. When

Fig. 1 Illustration of a livability-oriented social environment



- the PHEP is higher, the community's social environment is better. Therefore, in theory, the PHEP is positively correlated with housing rents.
- 2) Occupation (denoted by the proportion of middle- and high-class occupations in the population; PMHCOP). In China, differences in occupational classes are embodied by the amount of organizational, economic, and cultural resources each class possesses; occupational class further determines a resident's social status and income. Occupations in China can be divided into the following classes: (1) management (managers in government departments and other publicly funded agencies, nonprofit organizations, and corporations), (2) professionals, (3) clerks and administrative staff, (4) workers in the retail and service sectors, (5) industrial workers (operators of manufacturing and transportation equipment and related staff), (6) workers in the agricultural sector (including staff in the industries of agriculture, forestry, ranching, fishery, and water conservancy), and (7) unemployed. The first four can be designated middle- and high-class occupations. In theory, a higher proportion of middle- and high-class occupations in a community indicates a better social environment and higher housing rents.
 - 3) Unemployment (denoted by the unemployment rate; UR). The unemployment rate is an important indicator of the sense of security and attractiveness of a community. The unemployed are more likely to be disgruntled and to have a negative feeling towards society, which leads to behaviors that disrupt the orderliness of the community and infringe on personal and property rights. A rise in the unemployment rate usually leads to a higher crime rate (Raphael & Winter-Ebmer, 2001). In addition, communities with a higher unemployment rate tend to have lower overall income and occupation classes, so residents in these communities have a limited ability to pay rent. Therefore, a higher unemployment rate indicates a less favorable social environment and lower housing rents.
 - 4) Floating population (denoted by the proportion of the population that is floating; PFP). The floating population affects the social environment in two aspects. On the one hand, the floating population is a sign of a region's vitality and attractiveness. In China, more advanced cities have a higher proportion of the population that is floating. In this context, the floating population has a positive impact on the social environment. From the safety perspective, however, the proportion of the floating population has a clear connection with the crime rate. A higher proportion of the floating population leads to higher crime rates (Cahill & Mulligan, 2007; Jiang et al., 2013). Therefore, communities with higher concentrations of floating populations are comparatively less safe. When the floating population proportion in a community is higher, the social environment is worse. This phenomenon means that, theoretically, the floating population has both positive and negative impacts on the social environment and, therefore, on housing rents. From the perspective of the demand for rental housing, however, as the floating population is more likely to rent, its proportion will probably raise housing rents. Thus, theoretically, the proportion of the floating population is more likely to be positively correlated with housing rents.
 - 5) Rental household (denoted by the proportion of households that are renting; PRH). Ownership of residential property rights is a major determinant of residents' social status (Saunders, 1978). With the rapid rise in housing prices, the

wealth gap has been widened between residents who own housing properties and those who do not, creating social stratification (Huang & Jiang, 2009; Yi & Huang, 2014). Rental households do not own property, and their social stratum tends to be lower than that of households who own their homes. Research indicates that a higher proportion of rental housing in a community is correlated with higher violent crime rates, such as homicides and robbery (Lockwood, 2007). This situation occurs because, on the one hand, residents who live in rental housing usually earn lower incomes and belong to the more vulnerable groups of our society; they are more likely to commit crimes. Moreover, the population living in rental housing is usually less stable, which leads to reduced community safety. The proportion of rental households is an indicator of property ownership in a community, and a higher proportion of rental households indicates a less favorable social environment.

Study Area

Guangzhou is a Chinese megacity. It has an active residential rental market, and renters account for a high portion of its population. More importantly, its social structure has significant spatial variance. Therefore, we select the Guangzhou metropolis as our study area (Fig. 2). Its land area is 1,409 square kilometers, and its population is 8.28 million (based on a tabulation of population data collected through the sixth census of the Guangzhou Municipality). Based on the city's characteristics and urban development trends, the study area is divided into four functional categories:

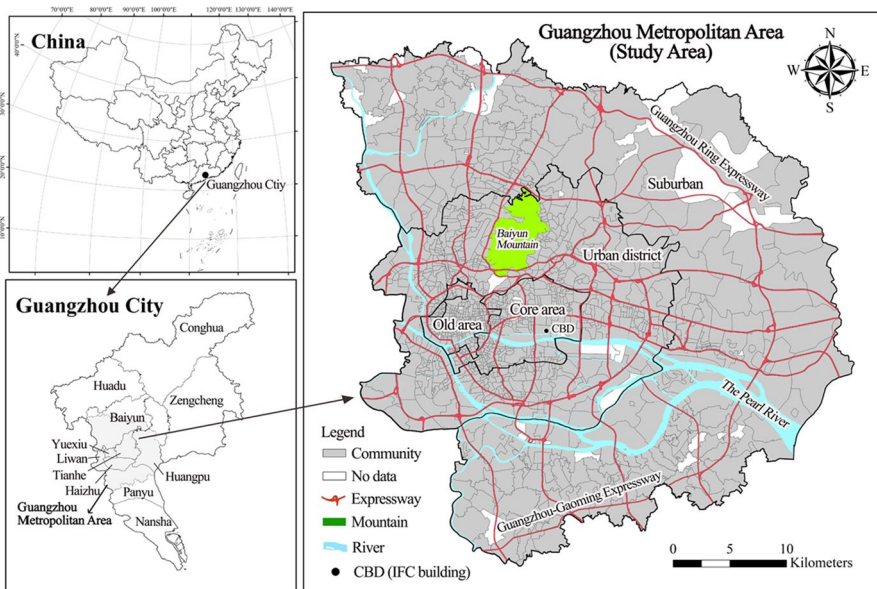


Fig. 2 Study area

the core and historic areas as well as the urban and suburban districts (Wang et al., 2020). The study area includes 1,364 communities, of which 1,328 (for which housing rental data are available) are selected as the subjects for our study. The Zhujiang New Town is located in Guangzhou's CBD, and the International Finance Centre (IFC) is located at the center of the CBD.

Research Design

This paper develops a research framework to analyze spatial heterogeneity in the social environment's impact on housing rents, as well as the direction and extent of this impact. The paper further compares the impacts of different social environmental factors on housing rents. The analytical process is as follows. First, we use the data of the 1,328 communities of the Guangzhou metropolitan area and construct a housing rental influencing factor model from the perspectives of the social environment (including the above five indicators) as well as the building, convenience, physical environmental, and location characteristics. Second, we use an ordinary least squares (OLS) model to examine the global factors that impact housing rents in Guangzhou and to examine the directions of the impacts. Third, we apply the GWR model to perform geographical variability tests on the local coefficients of the variables to distinguish the local from the global variables. Fourth, we apply a mixed GWR to explore spatial heterogeneity in the social environment's impact on housing rents. Specifically, this examination covers spatial heterogeneity in terms of the significance, direction, and strength of the social environment's impact on housing rents. Last, the research findings are analyzed (Fig. 3).

The average housing rents of the communities, which are derived from the sixth census of Guangzhou Municipality, are the dependent variable in the regressions. The census data provide the number of households in the housing rent intervals for each community; the average rent of the community can be calculated from these data. The five factors of the social environment are the explanatory variables explained above. In addition, the building, convenience, physical environmental, and location characteristics are the control variables, and they consist of the following indicators:

- Building characteristics: building age (BAGE), building area per household (BAREA), and building interior facilities (BIF) are the three main indicators of the building characteristics (Goodman & Thibodeau, 2003; Phe & Wakely, 2000; Stevenson, 2004; Wittowsky et al., 2020). In theory, newer buildings, larger building areas, and better facilities usually generate higher rents.
- Convenience characteristics: these characteristics are analyzed from the perspectives of work and shopping convenience (WSC) and social public service convenience (SPSC). WSC includes access to office space, subway stations, and stores; SPSC includes the convenience of basic education, medical services, and cultural and physical amenities. Empirical research has found that convenience concerns heavily affect residential location choices (Cervero & Wu, 1997; Kim

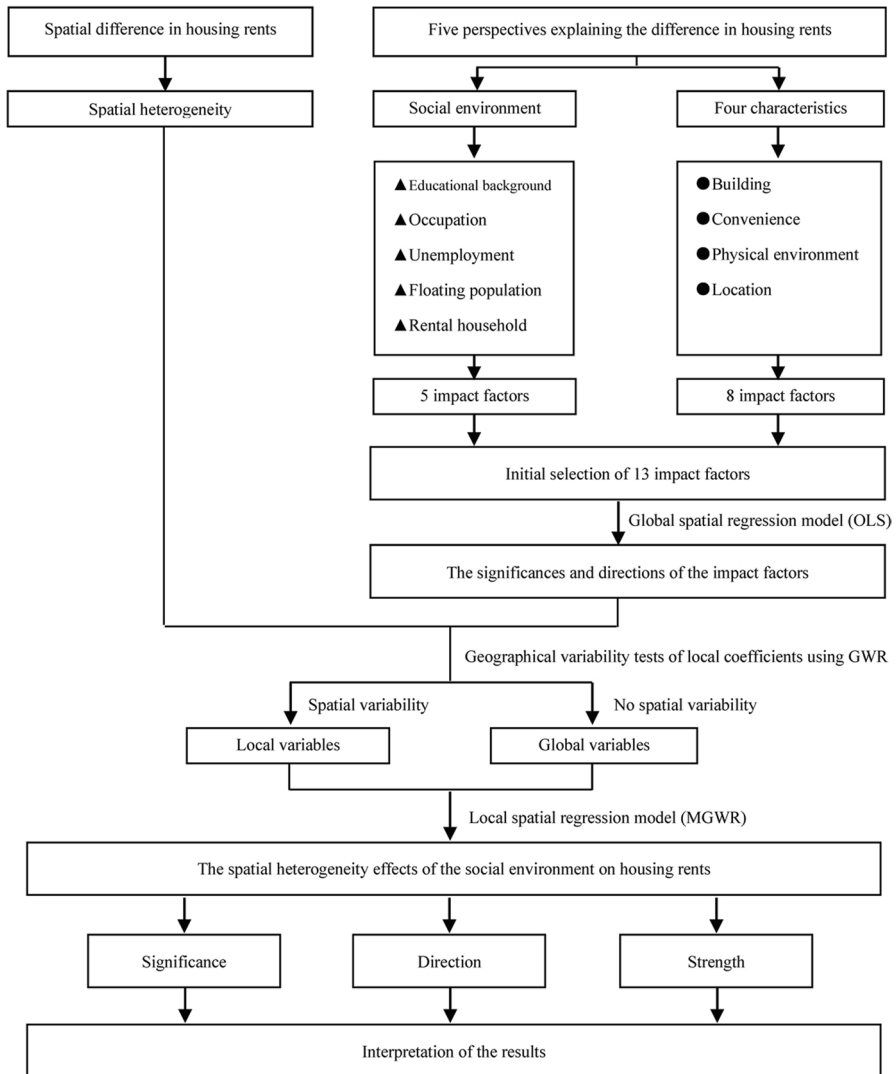


Fig. 3 Research design. In the Figure, please make the following changes

et al., 2005; Humphreys & Ahern, 2019) and form a critical component of the hedonic price model (Cao et al., 2019; Qin & Han, 2013; Yang et al., 2018).

- Physical environmental characteristics: physical environmental characteristics include positive and negative physical environments (PPE and NPE) (Wang et al., 2020). In terms of the PPE, empirical research indicates that parks (Czembrowski & Kronenberg, 2016), waterfronts (Kim et al., 2019), and famous landmarks (Chu & Wen, 2018) are elements of a superior physical environment, and they play a positive part in residents’ choice of a housing location, thus theoretically raising housing rents. Elements that constitute an NPE include transportation facilities,

municipal facilities, and factories. These facilities tend to have a negative impact on the environment (Rava et al., 2011). Transportation facilities include transportation centers (e.g., airports, train stations, and coach stations) and major transportation corridors that affect the environment (e.g., highways, elevated roads, and railways). Typical municipal facilities include high-voltage corridors, signal transmission towers, funeral homes, gas stations, substations, sewage treatment plants, and garbage disposal sites. Transportation and municipal facilities may have drawbacks related to air quality, smell, radiation, hygiene, noise, and safety, thereby reducing housing values (Banfi et al., 2008; Brasington & Hite, 2005; Diao et al., 2016; Gurran & Phibbs, 2017; Nelson et al., 1992). Factories may cause noise and air pollution to the surrounding areas and yield a landscape with negative values, so they also decrease housing values (Li & Brown, 1980; Wang et al., 2015). Theoretically, an NPE is negatively correlated with housing rents.

- Location characteristics: location is an important consideration when making housing choices (Schirmer et al., 2014). CBD accessibility is the indicator cited most often among location characteristics (Wang et al., 2020; Wu et al., 2015). In theory, when a housing location is closer to the CBD, it is superior, and its rents are higher.

The specific definitions, calculation methods, and index compositions of the variables are shown in Table 1. The scores of the variables are calculated through weighted sums.

The evaluation standard (score) or calculation method of each control variable is given in Table 2. For the compound variables (e.g., BIF, WSC, SPSC, PPE, and NPE), the weights of the indicators are calculated through a factor analysis, and the weighted sum is employed to calculate their scores. We used a positive standard deviation (sd) value examination to evaluate the agglomeration level of the indicators. The details for determining the threshold are shown in Table 2. This evaluation method is also used widely in the field of housing prices and industry research (Ye et al., 2019a, b).

Data and Data Sources

The data for housing rent, the social environment (PHEP, PMHCOP, UR, PFP, and PRH), and building characteristics (BAGE, BAREA, and BIF) are calculated from the tabulation of the sixth population census of the Guangzhou Municipality, calculated in November 2010. The PPE data, obtained in 2011, are obtained from a vectorized drawing of the “Outline of the Guangzhou Urban Master Plan (2011–2020).” The data for WSC, SPSC, the NPE, and the CBD are based on the Guangzhou point of interest (POI) database from 2012. Since both the PPE and POI data are relatively stable and do not change much in the short term, they can be used as control variables.

Methods

Traditional regression models can measure only the significance and direction of influencing factors on a global scale. Considering the spatial heterogeneity of housing rents and the influencing factors, these regression analyses are insufficient. The

Table 1 Definitions and evaluation methods for the variables

Variable (Symbol)	Evaluation method or index composition	Expected direction
Dependent variable: Housing rent (HR)	Estimated value of the average housing rent of the community (yuan per house per month)	
Explanatory Variables—Social Environment		
Proportion of highly educated population (PHEP)	PHEP among those aged six years and above expressed as a percentage	+
Proportion of middle- and high-class occupation population (PMHCOP)	PMHCOP among the employed population expressed as a percentage; middle- and high-class occupations include (1) management (managers in government departments and other publicly funded agencies, nonprofit organizations, and corporations), (2) professionals, (3) clerks and administrative staff, and (4) workers in the retail and service sectors	+
Unemployment rate (UR)	Proportion of unemployed population among economically active people (employed population plus unemployed population) expressed as a percentage	-
Proportion of floating population (FPF)	FPF among total population expressed as a percentage	±
Proportion of rental household (PRH)	PRH among total households expressed as a percentage	-
Control Variables—Building, Convenience, Physical Environmental, and Location Characteristics		
Building age (BAGE)	Score of the average BAGE	-
Building area per household (BAREA)	Score of the average BAREA	+
Building interior facilities (BIF)	Comprehensive score for the availability and type of cooking fuel, pipe water, kitchen, toilet, and bathing facilities	+
Work and shopping convenience (WSC)	Comprehensive score for the accessibility to office space, subway stations, and stores	+
Social public services convenience (SPSC)	Comprehensive score for the conveniences of basic education, medical services, and cultural and physical amenities	+
Positive physical environment (PPE)	Comprehensive score for the accessibility to famous landmarks, waterfronts, and parks	+
Negative physical environment (NPE)	Comprehensive score for the proximity to distasteful municipal facilities and factories	-
Distance from the CBD (DCBD)	Distance from the IFC (m)	-

GWR model is also used widely in the housing prices research to analyze the impact of variables at the local level (Agudelo Torres et al., 2015; Tomal, 2020). However, it cannot distinguish further between global and local factors. Therefore, we adopted Mixed GWR, which is used less in housing studies, to distinguish local from global variables. This combination of the OLS and Mixed GWR models can reveal more accurately the impact of the social environmental factors on the housing price.

Table 2 Evaluation standard (score) or calculation method for the control variables

Variable (Symbol)	Definition	Evaluation standard (score) or calculation method
Control Variables—Building Characteristics		
Building age (BAGE)	Community score of the average BAGE	After 2000 (1), 1990–1999 (3), 1980–1989 (5), 1970–1979 (6) 1960–1969 (7), 1949–1959 (8), or before 1949 (9). The proportion of households that live in buildings constructed in each of the time periods listed above is calculated; these values are multiplied by the corresponding scores and then summed. (The variables BAREA and BIF below are calculated in the same manner.)
Building area per household (BAREA)	Community score of the average BAREA	Over 200 m ² (9), 140–200 m ² (8), 110–140 m ² (7), 80–110 m ² (6), 50–80 m ² (4), 20–50 m ² (3), 10–20 m ² (2), or less than 10 m ² (1)
Building interior facilities (BIF)	Cooking fuel	Gas (9) or no gas available (electricity, coal, firewood, or other) (1)
	Pipe water	Tap water (9) or no tap water (1)
	Kitchen	Independent kitchen (9), shared kitchen (5), or no kitchen (1)
	Toilet	Independent use of toilet (9), shared toilet, (5) independent other forms of toilet (3), or shared other forms of toilet (1)
	Bathing facilities	Uniform hot water supply or home-installed water heaters (9), other forms of bathing facilities (5), or no bathing facilities (1)
Control Variables —Convenience Characteristics		
Work and shopping convenience (WSC)	Office space accessibility	Positive sd value examination of the kernel density distribution of business office space (including office buildings, institutions, and government agencies) divided into five levels: community located outside the mean (1) or community located at the mean–1 sd (3), 1–2 sd (5), 2–3 sd (7), or 3 sd (9)
	Subway station accessibility	Distance to subway stations and score assigned: over 1,500 m (1), 800–1,500 m (3), 400–800 m (5), 200–400 m (7), or less than 200 m (9)
	Store accessibility	Positive sd value examination of the kernel density distribution of stores (including shopping malls, supermarkets, and convenience stores) divided into five levels: community located outside the mean (1) or community located at the mean–1 sd (3), 1–2 sd (5), 2–3 sd (7), or 3 sd (9)
Social public service convenience (SPSC)	Basic educational convenience	Provincial key elementary school located within the community (9); municipal key elementary school located within the community (7); or other communities without provincial or municipal key elementary schools within 500 m from provincial or municipal key elementary schools (5), within 500 m of ordinary elementary schools (3), or 500 m from all primary schools (1)

Table 2 (continued)

Variable (Symbol)	Definition	Evaluation standard (score) or calculation method
	Medical service convenience	Over 2,000 m away from all hospitals (1), over 2,000 m away from third-class hospitals and within 2,000 m of general hospitals (5), or within 2,000 m of third-class hospitals (9)
	Cultural and physical activity convenience	Number of major stadiums, science and technology centers, museums, libraries, cultural centers, and youth activity centers within 1,000 m of the community: 0–1 (1), 2–3 (2), 4–5 (3), 6–7 (4), 8–9 (5), 10–14 (6), 15–19 (7), 20–24 (8), or ≥ 25 (9)
Control Variables—Physical Environmental Characteristics		
Positive physical environment (PPE)	Famous landmark accessibility	Distance to famous landmarks: within 500 m (9), 500–1,000 m (5), or over 1,000 m (1)
	Waterfront accessibility	Distance to rivers (lakes): within 200 m (9), 200–400 m (7), 400–800 m (3), or beyond 800 m (1)
	Park accessibility	Distance to parks: within 200 m (9), 200–400 m (7), 400–800 m (3), or over 800 m (1)
Negative physical environment (NPE)	Municipal facilities pollution	A pollution range is set for each of the municipal facilities as follows: garbage disposal field (4,000 m), sewage treatment plant (2,000 m), funeral home (1,000 m), substation (500 m), gas station (80 m), railway (80 m), coach station (500 m), railway station (500 m), and highway or elevated road (200 m). If a community is not located within any of the ranges above, it is assigned a score of 1; for each additional municipal facility that is located with the defined range from the community, the score increases by 1
	Factories pollution	Positive sd value examination of the kernel density distribution of factory divided into five grades: community located outside the mean (1) or community located at the mean–1 sd (3), 1–2 sd (5), 2–3 sd (7), or 3 sd (9)
Control Variables—Location Characteristics		
CBD accessibility (DCBD)	DCBD	Distance from the IFC (m)

OLS Model

The OLS model (global regression) is applied to analyze the factors that influence housing rents in Guangzhou. This analysis verifies whether the factors selected are reasonable and tests whether they have significant impacts on housing rents. The technique used most often to study the factors that influence housing rents is OLS regression. The OLS model can be used to analyze the global factors that influence

housing rents in Guangzhou as well as the direction of the impact. The OLS model is expressed as follows:

$$y_s = \sum_{i=1}^n \beta_i x_{si} + \beta_0 + \varepsilon_s, \quad [\varepsilon_s \sim N(0, \delta^2)] \tag{1}$$

where s (1,...,1328) denotes the Guangzhou communities, y_s refers to housing rent in the s^{th} community, β_i is the regression coefficient, x_{si} ($i=1, \dots, 13$) denotes the variables of the factors influencing housing rents, β_0 is a constant term, and ε_s denotes the error of the housing rent model. $\varepsilon_s \sim N(0, \delta^2)$ indicates that the error term follows a normal distribution and its variance is consistent; the product of the error and the covariance matrix is 0. The dependent and independent variables of this work are standardized by taking the natural logarithm.

Mixed Geographically Weighted Regression

The OLS model can include all of the data used in one equation (Wang et al., 2017) and assumes this statistical relationship is consistent anywhere. The GWR model allows the relationship between the dependent and the independent variables to have local spatial variance within the entire space (Bitter et al., 2007; Cellmer et al., 2020; Hanink et al., 2012). The GWR model is similar to the OLS model, but the OLS model is expanded by embedding the observed geographic locations into the model. Each parameter is estimated based on space and varies with spatial changes (Brunsdon et al., 1996), greatly increasing the model’s goodness of fit. Under certain circumstances, however, not every regression coefficient will have local spatial changes. Global and local variables can coexist. In this case, the mixed geographically weighted regression (mixed GWR) model is a better fit. The mixed GWR model combines the GWR model with global multiple regression. Certain parameters, corresponding to global variables, are set as constant, while other parameters, corresponding to local variables, are set as variable (Brunsdon et al., 1999). The parameters are estimated with a two-phase reiteration method. The basic form of the mixed GWR model is as follows:

$$y_s = \sum_{i=1}^n \alpha_i x_{si} + \beta_0(u_s, v_s) + \sum_{i=n+1}^m \beta_i(u_s, v_s) x_{si} + \varepsilon_s, \quad [\varepsilon_s \sim N(0, \delta^2)] \tag{2}$$

where α_i and β_i are the regression coefficients of the global and the local variables, respectively, of the i^{th} variable. (u_s, v_s) represents the geographic coordinates of community s . Consequently, $\beta_0(u_s, v_s)$ is a constant term, with $\beta_i(u_s, v_s)$ being the local regression coefficient of the i^{th} variable for community s . ε_s is the error term. The data for the dependent and independent variables are processed by logarithmic standardization.

The weighted OLS technique is applied to estimate the elasticity coefficient of any community (u_s, v_s) . The estimated value is as follows:

$$\hat{\beta}(u_s, v_s) = (X^T W(u_s, v_s) X)^{-1} X^T W(u_s, v_s) y_s \quad (3)$$

where X is a variable matrix of the factors that influence housing rents, T denotes the matrix transpose operation, and $W(u_s, v_s)$ denotes a spatial weight matrix composed of the monotonically decreasing function value.

We use the bi-square kernel function of adaptive bandwidth to calculate the weights between Guangzhou's communities.

$$W_{sk} = \begin{cases} [1 - (d_{sk}/b_s)^2]^2, & k \in N_q(s) \\ 0, & k \notin N_q(s) \end{cases} \quad (4)$$

where W_{sk} is the spatial weight matrix between the positions of community s and community k ; b_s is the adaptive bandwidth, which is determined based on the number of neighboring communities; $N_q(s)$ denotes a set formed by the q communities that are closest to community s ; and W_{sk} is a continuous monotonically decreasing function of d_{sk} , such that, when $d_{sk}=0$, $W_{sk}=1$.

The communities are not distributed evenly across the study area. The communities in the old and core areas of Guangzhou are smaller, so they have a higher density. When the density of a community is higher, the bandwidth is smaller, and vice versa. To calculate the optimal bandwidth, we apply the adjusted value of the Akaike information criterion (AIC_C) (Mou et al., 2017). The AIC_C can be written as follows:

$$AIC_C = 2m \ln \hat{\sigma} + m \ln(2\pi) + \frac{m + tr(S)}{m - 2 - tr(S)} \quad (5)$$

where σ represents the maximum likelihood estimate of the variance of the random error, and $tr(S)$ is the trace of the S matrix.

Results

Spatial Heterogeneity of the Housing Rents

The descriptive statistics of the housing rents are presented in Fig. 4. Based on the Jenks natural breaks classification method, five data intervals are created: ≤ 510.20 yuan, 510.21–917.74 yuan, 917.75–1,475.00 yuan, 1,475.01–2,290.90 yuan, and $> 2,290.90$ yuan. The number of communities in each interval is 560, 374, 226, 115, and 53, respectively. Figure 5 presents the spatial heterogeneity pattern of housing rents in Guangzhou as drawn by ArcGIS 10.0. The communities with a rent above 1,475.00 yuan are mainly located in the core area. Overall, the core area has the highest rent value of close to 1,150.93 yuan. That of the urban district is 844.31 yuan, and that of the historical district is 592.10 yuan. The suburban district has the lowest rent value at 522.50 yuan.

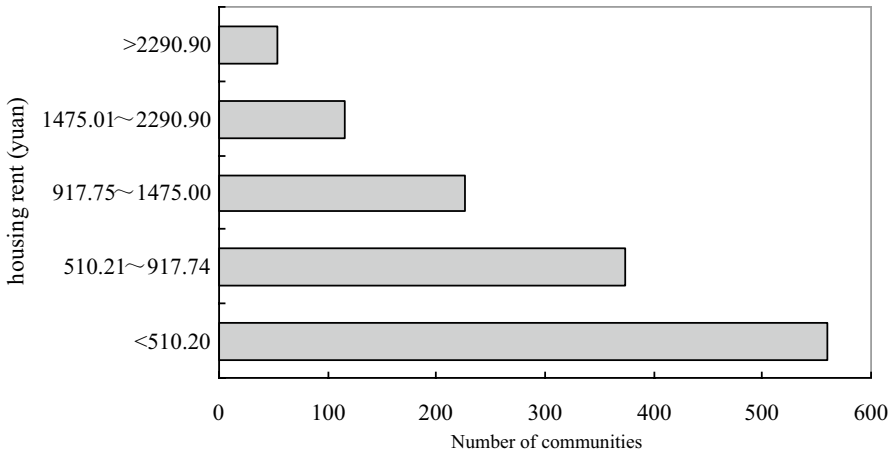


Fig. 4 Descriptive cluster statistics of housing rents

Spatial Heterogeneity of the Social Environment

The five social environmental indicators (PHEP, PMHCOP, UR, PFP, and PRH) are sorted into five classes using the natural breaks (Jenks) method (Fig. 6). A higher score indicates a better social environment. The communities with a PHEP score of higher than 31.09% are mainly located in the core area, the pie-shaped area northeast of the urban district, and the university town in the suburban district. The communities with a higher PMHCOP score are mainly in the core area, the old area, and the north side of the urban district; the PMHCOP score in the university town of the suburbs is generally high, with most communities scoring above 76.92%. In terms of the UR, the communities with a higher unemployment rate (above 11.49) are mainly distributed in the old area and the suburbs. Regarding the PFP, the communities in the core and old areas generally have a low PFP score, with most communities scoring below 32.98%. For the PRH, the communities that score above 48.89% are mainly on the south side of the old area, the south and east sides of the urban district, and the suburbs. Overall, the spatial distribution is heterogeneous for the five indicators of the social environment.

Social Environmental Effects on Housing Rents Based on the OLS Model

The OLS model is employed to analyze whether the social environment has an overall impact on housing rents as well as the extent and direction of this impact. First, we perform a multicollinearity test for all the indicators with SPSS19.0 (Table 3). The result indicates that the 13 indicators do not have multicollinearity, so all are incorporated in the OLS model. Further, the normality of the standardized residuals of the OLS model is tested, and all residuals follow a normal distribution, indicating a high degree of accuracy for the regression model.

The OLS model results show an adjusted R^2 and an AIC of 0.6586 and 1445.39, respectively. Of the 13 indicators, 11 are correlated significantly with housing rents

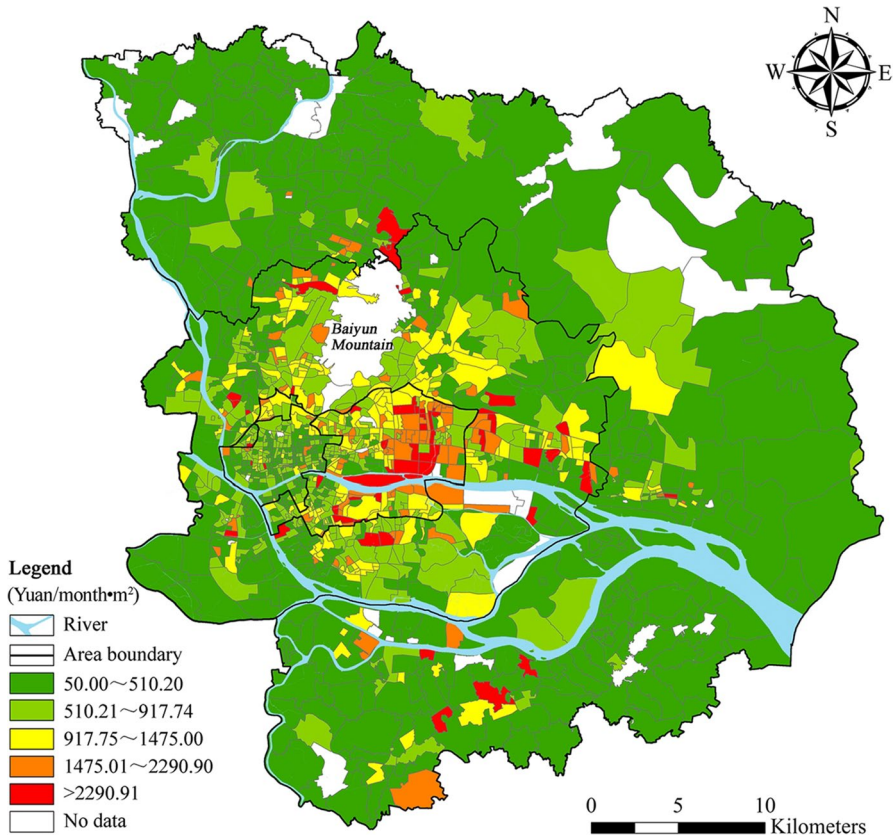


Fig. 5 The spatial heterogeneity pattern of the housing rents in Guangzhou using the natural breaks (Jenks) method

(at the 0.05 level), and the directions of the impacts are consistent with the theoretical predictions (Table 3). For every 1% increase in the PHEP, PMHCOP, and PFP, the rent increases by 0.0693%, 0.3085%, and 0.3587%, respectively. For every 1% increase in the UR and PRH, the rent decreases by 0.0421% and 0.2775%, respectively. These results indicate that, at the global level, the five indicators of the social environment all have statistically significant impacts on the rent and that the directions of the impacts coincide with the predictions.

Regarding the controlling factors, BAGE, BAREA, BIF, WSC, SPSC, and DCBD have statistically significant impacts on rents, and the directions of these impacts are consistent with the theoretical predictions. Neither the PPE nor the NPE significantly impact rents. In summary, building, convenience, and location characteristics have significant impacts on rents, but the physical environment does not at the global level.

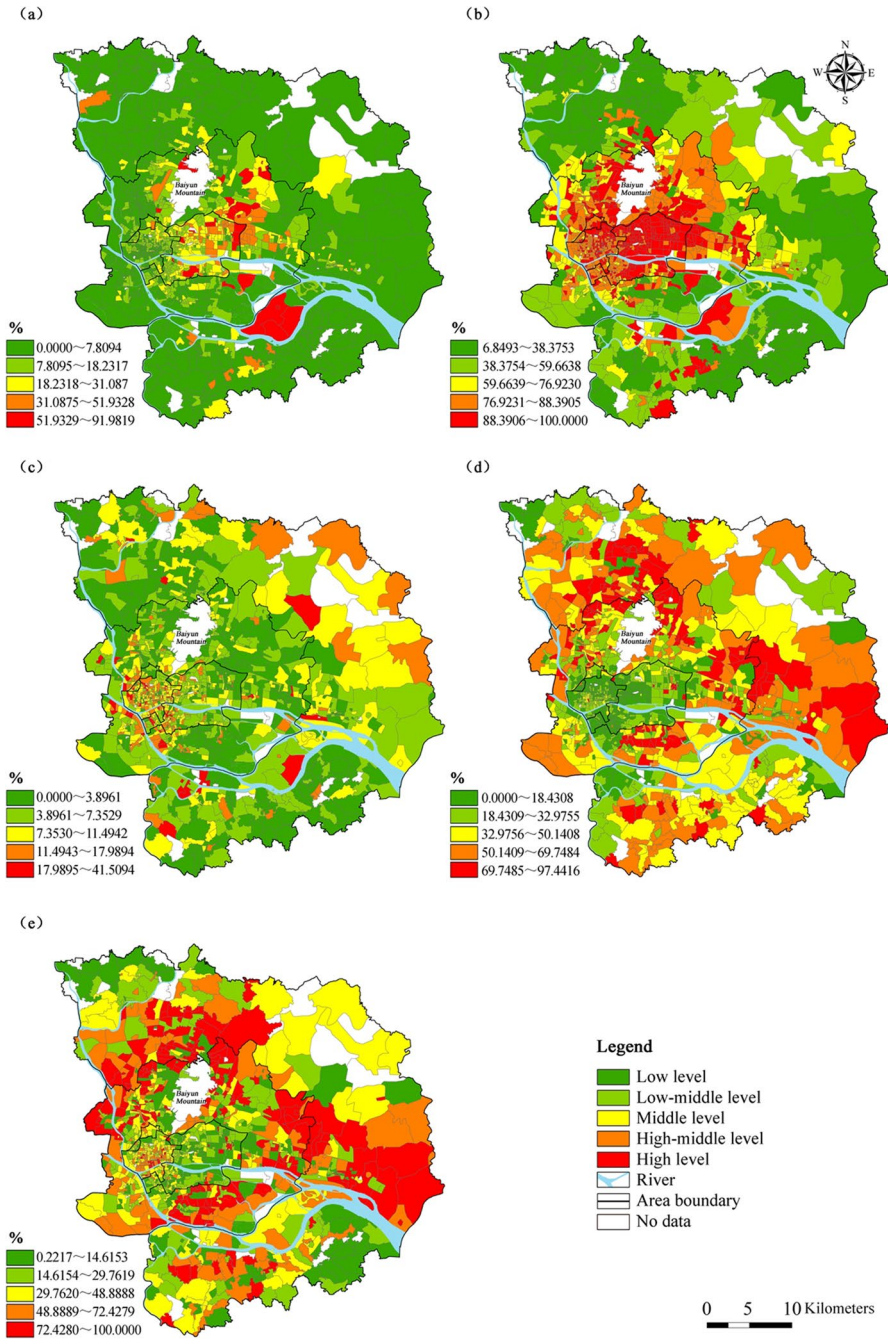


Fig. 6 The spatial heterogeneity pattern of the social environment in Guangzhou using the natural breaks (Jenks) method

Table 3 OLS model results

	Coefficient	Std. error	t/z-value	P	Tolerance	VIF
Intercept	3.8727	0.5639	6.8682	0.0000		
PHEP	0.0693***	0.0171	4.0526	0.0001	0.2981	3.3551
PMHCOP	0.3085***	0.0455	6.7738	0.0000	0.3382	2.9571
UR	-0.0421**	0.0165	-2.5470	0.0110	0.6741	1.4835
PFP	0.3587***	0.0225	15.9338	0.0000	0.4258	2.3483
PRH	-0.2775***	0.0196	-14.1697	0.0000	0.3594	2.7828
BAGE	-0.1735***	0.0333	-5.2092	0.0000	0.5562	1.7979
BAREA	0.3379***	0.0815	4.1441	0.0000	0.3628	2.7562
BIF	1.2135***	0.2189	5.5427	0.0000	0.5147	1.9428
WSC	0.1624***	0.0244	6.6536	0.0000	0.3865	2.5873
SPSC	0.1365***	0.0345	3.9579	0.0001	0.4783	2.0906
PPE	0.0261	0.0240	1.0901	0.2759	0.7767	1.2875
NPE	0.0198	0.0210	0.9416	0.3466	0.9069	1.1027
DCBD	-0.2663***	0.0262	-10.1583	0.0000	0.5365	1.8639

R²: 0.6623; adjusted R²: 0.6587; log-likelihood: -707.70; AICc: 1,445.39

*, **, and *** represent the 0.01, 0.05, and 0.1 significance levels, respectively

Impact of Spatial Heterogeneity in the Social Environment on the Housing Rents Using the Mixed GWR Model

Housing rent patterns in Guangzhou are spatially heterogeneous. Therefore, we must employ the local spatial regression model (e.g., GWR) to analyze further the heterogeneity of the social environment's impact on housing rents. However, not all of the independent variables are local regression variables; some may be global variables. Therefore, geographical variability tests are required of the local coefficients for the 13 independent variables. We use GWR4.0 software to run the GWR model and select spherical coordinates. The Gaussian model is employed. The adaptive bi-square method is used to determine the geographic kernel type. A golden section search algorithm is used to calculate the bandwidths. The AICc is adopted as the criterion for the optimal bandwidth. The geographical variability tests of the local coefficients results are in Table 4. If the Diff of Criterion is positive, then the variable's coefficient has no spatial variability, and the variable should be treated as global; otherwise, the variable is local. The results indicate that WSC, SPSC, the UR, the PPE, and the NPE have a positive Diff of Criterion; as such, the five variables should be incorporated into the mixed GWR model as global variables. The other eight variables are incorporated into the mixed GWR model as local variables. Overall, the impact of the convenience and physical environmental characteristics on the housing rents does not show apparent spatial heterogeneity, while the impact of the social environment as well as the building and location characteristics does. The impact of the UR—an indicator of the social environment—on housing rents is also global and does not show apparent spatial heterogeneity.

Table 4 Geographical variability tests of the local coefficients

	F	DOF for F test	Diff of Criterion	Local or global coefficients
Intercept	3.4415	11.7730	-14.4175	
PHEP	2.4761	14.1610	-1.6606	Local
PMHCOP	5.1874	13.6180	-43.2732	Local
UR	0.9674	14.0690	22.8891	Global
PFP	3.0166	12.6750	-9.3465	Local
PRH	5.2558	12.7630	-41.6451	Local
BAGE	2.6357	13.3390	-4.0113	Local
BAREA	3.3915	13.4150	-15.5905	Local
BIF	7.6149	13.9420	-81.2858	Local
WSC	2.2285	11.2800	1.8776	Global
SPSC	1.4375	15.0890	16.2726	Global
PPE	1.3109	13.7440	16.8691	Global
NPE	1.3973	12.8520	14.5009	Global
DCBD	2.4675	7.8740	-0.8780	Local

The positive value of the Diff of Criterion (AICc) suggests no spatial variability in terms of model selection criteria. F test: in the case of no spatial variability, the F statistic follows the F distribution (per degrees of freedom, DOF) for the F test.

Based on the test results for the variables, a mixed GWR model is constructed. The model parameters are set in the same way as for the traditional GWR model, but the global and local variables are differentiated. The best bandwidth calculated by the model is 132.000. Table 5 compares the results of the three models: OLS, GWR, and mixed GWR. The mixed GWR model produces the highest adjusted R^2 and log-likelihood and the lowest AICc, an indication that the mixed GWR is better at explaining the relationship between the social environment and housing rents.

A summary of the coefficients of the eight local variables produced by the mixed GWR is presented in Table 6.

For the mixed GWR model, the spatial distribution of the local R^2 values that affect housing rents are shown in Fig. 7. The local R^2 values are divided into five intervals using the natural breaks (Jenks) method. They range from 0.2486 to 0.9266. In general, the local R^2 values measured in the northwest section of the core area and the old area are relatively low; in comparison, the values are high in the urban and suburban districts (the R^2 for most communities is above 0.7873). This result means that, in the urban and suburban districts, the influencing factors established in this paper have stronger power to explain the housing rents.

Table 5 comparison of the OLS, GWR, and mixed GWR models.

	R^2	Adjusted R^2	AICc	Log-likelihood
OLS	0.6623	0.6587	1,445.76	-707.70
GWR	0.7848	0.7302	1,300.94	-408.58
Mixed GWR	0.8067	0.7520	1,221.97	-337.32

Table 6 Statistics of the local coefficients of the mixed GWR model

	Min	Lower quartile	Median	Upper quartile	Max	STD
Intercept	-19.7713	-3.0720	2.3351	5.8364	14.6421	6.6037
PHEP	-0.3552	-0.0826	0.0206	0.0975	0.2946	0.1335
PMHCOP	-1.4843	0.0675	0.2504	0.9224	3.3361	0.6337
PFP	-0.0288	0.2044	0.2952	0.4091	0.6877	0.1517
PRH	-0.8020	-0.3235	-0.2134	-0.1113	0.4233	0.1573
BAGE	-1.1481	-0.3234	-0.1570	-0.0329	0.3661	0.2154
BAREA	-1.3322	0.1750	0.7228	1.1890	2.4379	0.7517
BIF	-1.8561	0.7532	1.7873	2.6517	7.3296	1.4073
DCBD	-1.7176	-0.4970	-0.2402	-0.0411	1.4025	0.3379

R²: 0.8872; adjusted R²: 0.7520; log-likelihood: -337.32; AIC: 1,221.97

The correlation between housing rents and the eight factors are investigated using the mixed GWR model, and a pseudo-t-test ($p < 0.05$) is applied to examine the statistical significance of the parameters (Table 7). Of the four local variables of the social environment, the PHEP and the housing rent demonstrate a statistically significant positive correlation in 18.98% of the communities. This positive correlation also exists between the PMHCOP and the rent and between the PFP and the rent in 29.74% and 74.85% of the communities, respectively. The PRH and rent have a negative correlation in 62.95% of the communities (consistent with predictions). Therefore, of the four social environmental factors, the PFP affects the most communities, followed by the PRH.

The spatial distribution of the significance, extent, and direction of the correlations between the four factors of the social environment and housing rents are shown in Fig. 8. The estimated coefficients are divided into five categories based on quantiles. The areas that are not statistically significant are marked as gray. In terms of educational background, the communities in which the PHEP and housing rents show a significant positive correlation are mainly located in the suburban district; in terms of occupation, the communities in which the PMHCOP and housing rents are positively correlated are mainly located in the east and southwest sections of the core area (these areas show the most significant impacts) and in the suburban districts. In terms of the PFP, the communities in which the PFP and housing rents are positively correlated are mainly located in the historic area, in the center of the core area, on the west side of the urban district, and on the west side of the suburban district. In terms of the PRH, the communities where the PRH and HR are negatively correlated (consistent with predictions) are mainly located in the core area, the south and east sides of the urban district, and the suburban district. Therefore, we find spatial heterogeneity in the extent and direction of the social environment's impacts (other than unemployment) on the housing rents. In addition, the communities where the direction and extent of the impacts are similar are spatially clustered. Overall, the impact of the social environment on housing rents is more evident in the suburban district, followed by the core area and urban district. In the old area, this impact is not evident.

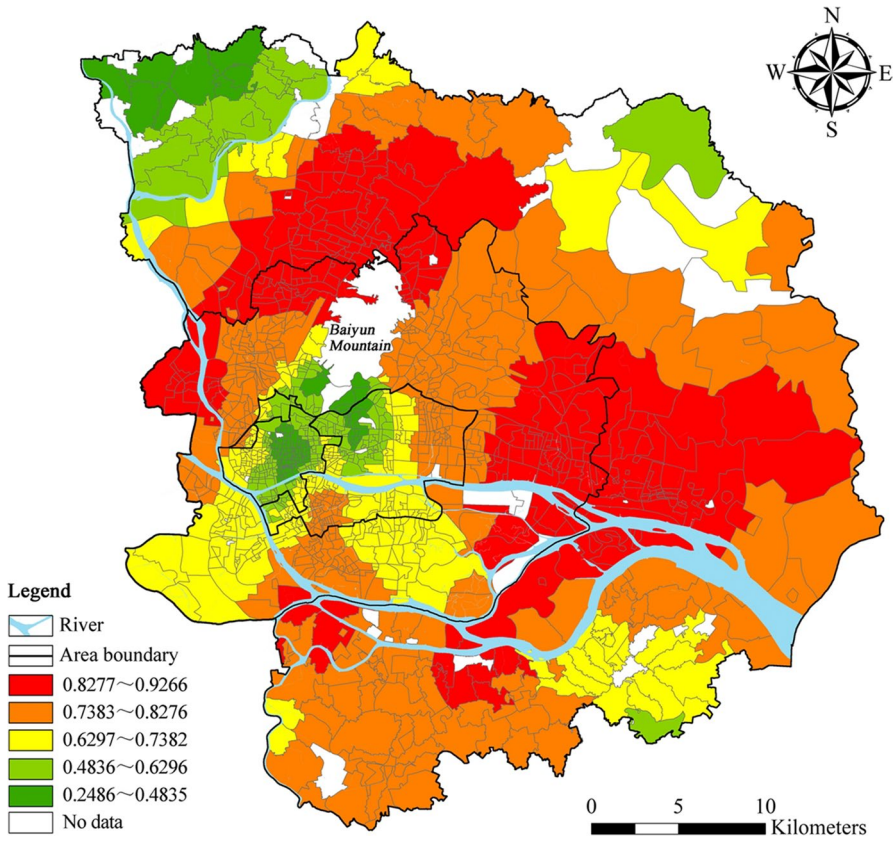


Fig. 7 The spatial distribution of the local R^2 factors affecting housing rents based on the mixed GWR model

Discussion and Conclusions

Discussion

Four environmental factors—educational background, occupation, floating population, and rental household—have significant impacts on housing rents ($p < 0.01$), and the directions of these effects are consistent with the theoretical predictions. Further, all of the impacts are spatially heterogeneous. Overall, the social environment affects housing rents, and the impact demonstrates spatial heterogeneity. Housing units with higher rents tend to have superior physical environmental characteristics and scarce city resources. The mechanism through which the social environment affects housing rents is as follows: in terms of affordability, higher rents amount to higher “thresholds.” People with higher educational levels and occupation classes have higher incomes and a greater ability to pay. Through space or price competition, they are more likely to secure housing in communities

Table 7 Statistical significance of the parameters of the local variables based on mixed GWR models of eight factors

	p < 0.05	+	-
PHEP	24.70%	18.98%	5.72%
PMHCOP	29.74%	29.74%	0.00%
PFP	74.85%	74.85%	0.00%
PRH	63.40%	0.45%	62.95%
BAGE	27.11%	0.08%	27.03%
BAREA	43.52%	43.30%	0.23%
BIF	42.55%	42.02%	0.53%
DCBD	35.54%	3.09%	32.45%

with higher rents. Residents who are not homeowners (rental households) tend to have lower social status than those who own residential properties. Therefore, rental households can afford less, and they are more likely to live in low-rent communities. From the perspective of supply and demand in the rental housing market, communities with a higher proportion of floating populations are more attractive and vigorous and have a higher demand for rental housing units. This phenomenon causes rents to increase. From the residential choice perspective, when the other housing characteristics (e.g., location and building characteristics) are the same, renters tend to choose communities with better social environments. Communities where the educational level and occupation classes are high and the proportion of rental households is low are more desirable. Therefore, communities with a better social environment have more intense competition for rental housing and higher rents.

To some extent, existing theories—such as the socio-spatial dialectic, housing class theory, and real property owner class theory—can substantiate the connection between housing rents and social space. The correlation between the social environment and housing rents has evident spatial heterogeneity. Therefore, the extent to which the mechanism is effective will inevitably demonstrate spatial heterogeneity. The findings of this paper indicate that the impact of the social environment on housing rents exists only in certain communities. Further, the impacts of the specific indicators that constitute the social environment on housing rents vary in terms of the range of the impacts and the communities where the impacts exist.

This paper develops a system to assess the factors shaping the livability-oriented social environment. Based on the OLS of the global regression model, the research tests the hypothesis that the social environment has a significant impact on housing rents. The educational background, occupation, floating population, and rental household proportions of a community significantly impact its housing rents. These findings are rarely mentioned in previous research. In addition, compared to previous research, this empirical analysis based on the mixed GWR model provides more detailed analyses of spatial heterogeneity in the social environment's impact on housing rents, with an emphasis on heterogeneity in the impacts of different social environmental

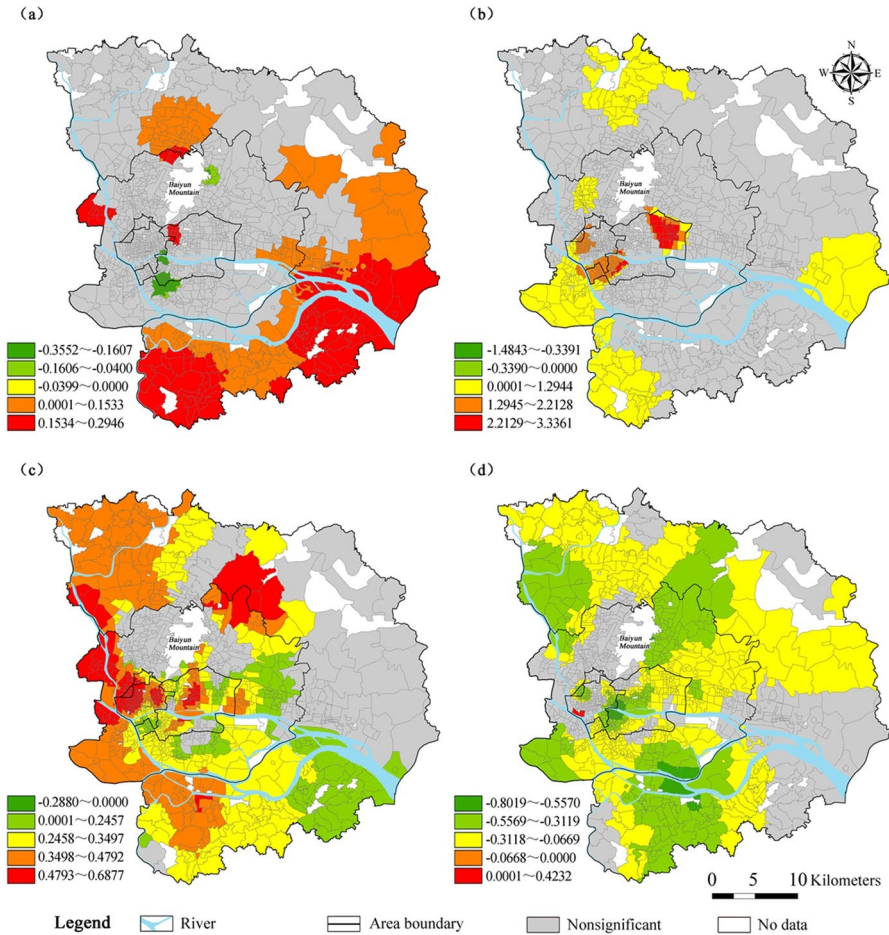


Fig. 8 The spatial distribution of the local parameter estimates of the social environment based on the mixed GWR model

indicators on housing rents. This topic has not widely examine in previous research. The significance of these findings is that they help to understand the spatial limitations of the factors (especially the social environment) that influence housing rents. In evaluating the housing rents in cities, the influence of the social environment should be considered, as should spatial heterogeneity and differentiations between indicators, making the evaluation more rational and scientific. Further, analyzing the heterogeneity in the relationship between the social environment and housing rents enables policy makers to develop evidence-based, spatially differentiated affordable rental housing programs and provides theoretical support for the development of livable cities.

Conclusions

This work develops a framework to examine the influencing factors of housing rents, including the social environment. It also develops datasets of the influencing factors of the housing rents for 1,328 communities in Guangzhou. Mixed GWR model is applied to analyze spatial heterogeneity in the social environment's impact on the housing rents. Specifically, we focus on the direction and extent of the impacts that the educational background, occupation, floating population, and rental household proportions may have on the housing rents.

The paper finds that the housing rents in Guangzhou demonstrate clear spatial heterogeneity. Overall, rents in the core area are the highest, while those in the historic and suburban districts are generally lower. Similarly, the social environment of Guangzhou shows spatial heterogeneity, with the core area demonstrating the highest-quality social environment. The spatial distributions are not homogeneous for the educational background, occupation, unemployment, floating population, and rental household proportions.

This research employs OLS to test the relationship between the social environment and housing rents as well as the significance of the relationship. The findings indicate that the five factors of the social environment have statistically significant impacts on housing rents, and the directions of the impacts coincide with the theoretical predictions. Of them, the PHEP, PMHCOP, and PFP have significant positive impacts on housing rents: for each 1% increase in these three indicators, the rent increases by 0.0693%, 0.3085%, and 0.3587%, respectively. The UR and PRH have significant negative impacts on housing rents: for each 1% increase in the UR and PRH, the rent decreases by 0.0421% and 0.2775%, respectively.

The results of the geographical variability tests of the local coefficients indicate that the impact of unemployment—one of the five factors of the social environment—on the housing rents does not have spatial heterogeneity. However, the other four factors—educational background, occupation, floating population, and rental household—have spatial heterogeneity in their impacts.

The mixed GWR model is employed to analyze spatial heterogeneity in the relationship between the four factors of the social environment and housing rents. The results show that mixed GWR model is superior to the GWR and OLS models, producing higher R^2 and log-likelihood values and a lower AIC. The four social environmental factors significantly impact housing rents in different numbers of communities. Specifically, floating populations and rental households have a significant impact in more communities than the other two factors, at 74.85% and 62.95% of all communities studied, respectively. The communities where the four factors of the social environment show a significant impact on the housing rents also demonstrate spatial clustering in their distribution, and the areas where the communities concentrate vary. In general, the social environment impacts the housing rents most significantly in the suburban district, followed by the core area and the urban district. In the old area, the impact is not significant.

Policy Implications

The conclusions of this study provide a reference for the precise supply of spatially differentiated affordable rental housing programs in China's megacities. First, when planning and deploying affordable rental housing programs, the government should ensure that a certain proportion of affordable rental houses is arranged in communities with high-quality social environments, so people have more opportunities to rent in high-quality social environments. Second, the government should promote the suburbanization strategy and promote the diffusion of high-level employment opportunities and high-quality public resources to the suburbs, thereby attracting the migration of highly educated people and a high-class occupation population from the core area to the suburbs, thereby improving its social environment and enhancing the quality of rental housing there. Third, when building new commercial houses, developers should build rental housing in a certain proportion and increase the proportion of rental housing in communities with a high proportion of renters (such as suburbs with strong rental demands) to fulfill the rental requirements.

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Declarations

Conflicts of Interest The authors have no conflicts of interest to declare.

References

- Agudelo Torres, J. E., Agudelo Torres, G. A., Franco Arbeláez, L. C., & Franco Ceballos, L. E. (2015). Efecto de un estadio deportivo en los precios de arrendamiento de viviendas: una aplicación de regresión ponderada geográficamente (GWR). *Ecos de Economía*, 19(40), 66–80. <https://doi.org/10.17230/ecos.2015.40.4>

- Banfi, S., Filippini, M., & Horehájová, A. (2008). Valuation of Environmental Goods in Profit and Non-Profit Housing Sectors: Evidence from the Rental Market in the City of Zurich. *Swiss Journal of Economics and Statistics*, 144(4), 631–654. <https://doi.org/10.1007/BF03399269>
- Basolo, V., & Yerena, A. (2017). Residential mobility of low-income, subsidized households: a synthesis of explanatory frameworks. *Housing Studies*, 32(6), 841–862. <https://doi.org/10.1080/02673037.2016.1240762>
- Bitter, C., Mulligan, G. F., & Dall'erba, S. (2007). Incorporating spatial variation in housing attribute prices: a comparison of geographically weighted regression and the spatial expansion method. *Journal of Geographical Systems*, 9(1), 7–27. <https://doi.org/10.1007/s10109-006-0028-7>
- Brasington, D. M., & Hite, D. (2005). Demand for environmental quality: a spatial hedonic analysis. *Regional Science and Urban Economics*, 35(1), 57–82. <https://doi.org/10.1016/j.regsciurbeco.2003.09.001>
- Brunsdon, C., Fotheringham, A. S., & Charlton, M. (1999). Some notes on parametric significance tests for geographically weighted regression. *Journal of Regional Science*, 39(3), 497–524. <https://doi.org/10.1111/0022-4146.00146>
- Brunsdon, C., Fotheringham, A. S., & Charlton, M. E. (1996). Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. *Geographical Analysis*, 28(4), 281–298. <https://doi.org/10.1111/j.1538-4632.1996.tb00936.x>
- Cahill, M., & Mulligan, G. (2007). Using geographically weighted regression to explore local crime patterns. *Social Science Computer Review*, 25(2), 174–193. <https://doi.org/10.1177/0894439307298925>
- Cao, K., Diao, M., & Wu, B. (2019). A Big Data-Based Geographically Weighted Regression Model for Public Housing Prices: A Case Study in Singapore. *Annals of the American Association of Geographers*, 109(1), 173–186. <https://doi.org/10.1080/24694452.2018.1470925>
- Cassel, E., & Mendelsohn, R. (1985). The choice of functional forms for hedonic price equations: Comment. *Journal of Urban Economics*, 18(2), 135–142. [https://doi.org/10.1016/0094-1190\(85\)90012-9](https://doi.org/10.1016/0094-1190(85)90012-9)
- Cellmer, R., Cichulska, A., & Belej, M. (2020). Spatial Analysis of Housing Prices and Market Activity with the Geographically Weighted Regression. *Isprs International Journal of Geo-Information*, 9, 380. <https://doi.org/10.3390/ijgi9060380>
- Cervero, R., & Wu, K. L. (1997). Polycentrism, commuting, and residential location in the San Francisco Bay Area. *Environment and Planning A*, 29(5), 865–886. <https://doi.org/10.1068/a290865>
- Chu, L., & Wen, H. (2018). Temporal and Spatial Effects of Urban Center on Housing Price — A Case Study on Hangzhou, China. *World Journal of Social Science Research*, 5, 89. <https://doi.org/10.22158/wjssr.v5n1p89>
- Cui, N., Gu, H., Shen, T., & Feng, C. (2018). The Impact of Micro-Level Influencing Factors on Home Value: A Housing Price-Rent Comparison. *Sustainability*, 10(12). <https://doi.org/10.3390/su10124343>
- Czembrowski, P., & Kronenberg, J. (2016). Hedonic pricing and different urban green space types and sizes: Insights into the discussion on valuing ecosystem services. *Landscape and Urban Planning*, 146, 11–19. <https://doi.org/10.1016/j.landurbplan.2015.10.005>
- D'Arcangelo, F. M., & Percoco, M. (2015). Housing rent and road pricing in Milan: Evidence from a geographical discontinuity approach. *Transport Policy*, 44, 108–116. <https://doi.org/10.1016/j.tranpol.2015.07.004>
- D, H. . (1973). *Social Justice and the City*. Johns Hopkins University Press.
- Diao, M., Qin, Y., & Sing, T. F. (2016). Negative Externalities of Rail Noise and Housing Values: Evidence from the Cessation of Railway Operations in Singapore. *Real Estate Economics*, 44(4), 878–917. <https://doi.org/10.1111/1540-6229.12123>
- Efthymiou, D., & Antoniou, C. (2013). How do transport infrastructure and policies affect house prices and rents? Evidence from Athens, Greece. *Transportation Research Part a-Policy and Practice*, 52, 1–22. <https://doi.org/10.1016/j.tra.2013.04.002>
- Gan, X., Zuo, J., Chang, R., Li, D., & Zillante, G. (2016). Exploring the determinants of migrant workers' housing tenure choice towards public rental housing: A case study in Chongqing, China. *Habitat International*, 58, 118–126. <https://doi.org/10.1016/j.habitatint.2016.10.007>
- Gilbert, A. (2016). Rental housing: The international experience. *Habitat International*, 54, 173–181. <https://doi.org/10.1016/j.habitatint.2015.11.025>
- Goodman, A. C., & Thibodeau, T. G. (2003). Housing market segmentation and hedonic prediction accuracy. *Journal of Housing Economics*, 12(3), 181–201. [https://doi.org/10.1016/s1051-1377\(03\)00031-7](https://doi.org/10.1016/s1051-1377(03)00031-7)



- Gurran, N., & Pibbs, P. (2017). When Tourists Move In: How Should Urban Planners Respond to Airbnb? *Journal of the American Planning Association*, 83(1), 80–92. <https://doi.org/10.1080/01944363.2016.1249011>.
- Han, Y., & Wu, X. (2020). Language policy, linguistic landscape and residents' perception in Guangzhou, China: dissents and conflicts. *Current Issues in Language Planning*, 21(3), 229–253. <https://doi.org/10.1080/14664208.2019.1582943>
- Hanink, D. M., Cromley, R. G., & Ebenstein, A. Y. (2012). Spatial Variation in the Determinants of House Prices and Apartment Rents in China. *Journal of Real Estate Finance and Economics*, 45(2), 347–363. <https://doi.org/10.1007/s11146-010-9262-3>
- Haurin, D. R., & Brasington, D. (1996). School quality and real house prices: Inter- and intrametropolitan effects. *Journal of Housing Economics*, 5(4), 351–368. <https://doi.org/10.1006/jhec.1996.0018>
- Huang, Y., & Jiang, L. (2009). Housing Inequality in Transitional Beijing. *International Journal of Urban and Regional Research*, 33(4), 936–956. <https://doi.org/10.1111/j.1468-2427.2009.00890.x>
- Humphreys, J., & Ahern, A. (2019). Is travel based residential self-selection a significant influence in modal choice and household location decisions? *Transport Policy*, 75, 150–160. <https://doi.org/10.1016/j.tranpol.2017.04.002>
- Jiang, S., Land, K. C., & Wang, J. (2013). Social Ties, Collective Efficacy and Perceived Neighborhood Property Crime in Guangzhou. *China. Asian Journal of Criminology*, 8(3), 207–223. <https://doi.org/10.1007/s11417-013-9167-1>
- Jiang, W., Feng, T., Timmermans, H., & Li, H. (2017). A gap-theoretical path model of residential satisfaction and intention to move house applied to renovated historical blocks in two Chinese cities. *Cities*, 71, 19–29. <https://doi.org/10.1016/j.cities.2017.06.021>
- Jim, C. Y., & Chen, W. Y. (2006). Impacts of urban environmental elements on residential housing prices in Guangzhou (China). *Landscape and Urban Planning*, 78(4), 422–434. <https://doi.org/10.1016/j.landurbplan.2005.12.003>
- Jun, M.-J., & Kim, H.-J. (2017). Measuring the effect of greenbelt proximity on apartment rents in Seoul. *Cities*, 62, 10–22. <https://doi.org/10.1016/j.cities.2016.11.002>
- Kim, H. N., Boxall, P. C., Adamowicz, W. L. (2019). Analysis of the economic impact of water management policy on residential prices: Modifying choice set formation in a discrete house choice analysis *Journal of Choice Modelling* 33 <https://doi.org/10.1016/j.jocm.2018.07.001>
- Kim, J. H., Pagliara, F., & Preston, J. (2005). The intention to move and residential location choice behaviour. *Urban Studies*, 42(9), 1621–1636. <https://doi.org/10.1080/00420980500185611>
- Kuroda, Y. (2018). The effect of school quality on housing rents: Evidence from Matsue city in Japan. *Journal of the Japanese and International Economies*, 50, 16–25. <https://doi.org/10.1016/j.jjie.2018.05.002>
- Leung, K. M., & Yiu, C. Y. (2019). Rent determinants of sub-divided units in Hong Kong. *Journal of Housing and the Built Environment*, 34(1), 133–151. <https://doi.org/10.1007/s10901-018-9607-4>
- Li, H., Wei, Y. D., & Wu, Y. (2019). Analyzing the private rental housing market in Shanghai with open data. *Land Use Policy*, 85, 271–284. <https://doi.org/10.1016/j.landusepol.2019.04.004>
- Li, M. M., & Brown, H. J. (1980). Micro-Neighborhood Externalities and Hedonic Housing Prices. *Land Economics*, 56(2), 125
- Li, S., Lyu, D., Huang, G., Zhang, X., Gao, F., Chen, Y. (2020). Spatially varying impacts of built environment factors on rail transit ridership at station level: A case study in Guangzhou China. *Journal of Transport Geography* 82 <https://doi.org/10.1016/j.jtrangeo.2019.102631>
- Lockwood, D. (2007). Mapping crime in Savannah - Social disadvantage, land use, and violent crimes reported to the police. *Social Science Computer Review*, 25(2), 194–209. <https://doi.org/10.1177/0894439307298935>
- McCord, M., Davis, P. T., Haran, M., McIlhatton, D., & McCord, J. (2014). Understanding rental prices in the UK: a comparative application of spatial modelling approaches. *International Journal of Housing Markets and Analysis*, 7(1), 98–128. <https://doi.org/10.1108/IJHMA-09-2012-0043>
- Mou, Y., He, Q., & Zhou, B. (2017). Detecting the Spatially Non-Stationary Relationships between Housing Price and Its Determinants in China: Guide for Housing Market Sustainability. *Sustainability*, 9(10). <https://doi.org/10.3390/su9101826>
- Muhammad, I. (2017). Disamenity impact of Nala Lai (open sewer) on house rent in Rawalpindi city. *Environmental Economics and Policy Studies*, 19(1), 77–97. <https://doi.org/10.1007/s10018-015-0136-z>

- Nakagawa, M., Saito, M., & Yamaga, H. (2007). Earthquake risk and housing rents: Evidence from the Tokyo Metropolitan Area. *Regional Science and Urban Economics*, 37(1), 87–99. <https://doi.org/10.1016/j.regsciurbeco.2006.06.009>
- Nelson, A. C., Genereux, J., & Genereux, M. (1992). Price Effects of Landfills on House Values. *Land Economics*, 68(4), 359
- Nishi, H., Asami, Y., & Shimizu, C. (2019). Housing features and rent: estimating the microstructures of rental housing. *International Journal of Housing Markets and Analysis*, 12(2), 210–225. <https://doi.org/10.1108/IJHMA-09-2018-0067>
- Phe, H. H., & Wakely, P. (2000). Status, quality and the other trade-off: Towards a new theory of urban residential location. *Urban Studies*, 37(1), 7–35. <https://doi.org/10.1080/0042098002276>
- Qin, B., & Han, S. S. (2013). Emerging Polycentricity in Beijing: Evidence from Housing Price Variations, 2001–05. *Urban Studies*, 50(10), 2006–2023. <https://doi.org/10.1177/0042098012471979>
- Raphael, S., & Winter-Ebmer, R. (2001). Identifying the effect of unemployment on crime. *Journal of Law & Economics*, 44(1), 259–283. <https://doi.org/10.1086/320275>
- Rava, M., Marcon, A., Girardi, P., Pironi, V., Silocchi, C., Ricci, P., et al. (2011). Proximity to wood factories and hospitalizations for respiratory diseases in children. *Science of the Total Environment*, 410, 80–86. <https://doi.org/10.1016/j.scitotenv.2011.09.078>
- Saunders, P. (1978). Domestic property and social class. *International Journal of Urban and Regional Research*, 2(1–3), 233–251. <https://doi.org/10.1111/j.1468-2427.1978.tb00749.x>
- Schirmer, P. M., van Eggermond, M. A. B., & Axhausen, K. W. (2014). The role of location in residential location choice models: a review of literature. *Journal of Transport and Land Use*, 7(2), 3–21. <https://doi.org/10.5198/jtlu.v7i2.740>
- Stevenson, S. (2004). New empirical evidence on heteroscedasticity in hedonic housing models. *Journal of Housing Economics*, 13(2), 136–153. <https://doi.org/10.1016/j.jhe.2004.04.004>
- Tomal, M. (2020). Modelling Housing Rents Using Spatial Autoregressive Geographically Weighted Regression: A Case Study in Cracow. *Poland. Isprs International Journal of Geo-Information*, 9(6), 346
- Wang, Y., Wang, S., Li, G., Zhang, H., Jin, L., Su, Y., et al. (2017). Identifying the determinants of housing prices in China using spatial regression and the geographical detector technique. *Applied Geography*, 79, 26–36. <https://doi.org/10.1016/j.apgeog.2016.12.003>
- Wang, Y., Wu, K., Qin, J., Wang, C., & Zhang, H. o. (2020). Examining Spatial Heterogeneity Effects of Landscape and Environment on the Residential Location Choice of the Highly Educated Population in Guangzhou, China. *Sustainability*, 12(9). <https://doi.org/10.3390/su12093869>
- Wang, Y., Zhao, L., Sobkowiak, L., Guan, X., & Wang, S. (2015). Impact of urban landscape and environmental externalities on spatial differentiation of housing prices in Yangzhou City. *Journal of Geographical Sciences*, 25(9), 1122–1136. <https://doi.org/10.1007/s11442-015-1223-6>
- Wittowsky, D., Hoekveld, J., Welsch, J., & Steier, M. (2020). Residential housing prices: impact of housing characteristics, accessibility and neighbouring apartments – a case study of Dortmund, Germany. *Urban, Planning and Transport Research*, 8(1), 44–70. <https://doi.org/10.1080/21650020.2019.1704429>
- Wu, J., Wang, M., Li, W., Peng, J., & Huang, L. (2015). Impact of Urban Green Space on Residential Housing Prices: Case Study in Shenzhen. *Journal of Urban Planning and Development*, 141(4). [https://doi.org/10.1061/\(asce\)up.1943-5444.0000241](https://doi.org/10.1061/(asce)up.1943-5444.0000241)
- Yang, L., Wang, B., Zhou, J., & Wang, X. (2018). Walking accessibility and property prices. *Transportation Research Part D-Transport and Environment*, 62, 551–562. <https://doi.org/10.1016/j.trd.2018.04.001>
- Ye, Y., Wu, K., Xie, Y., Huang, G., Wang, C., & Chen, J. (2019a). How firm heterogeneity affects foreign direct investment location choice: Micro-evidence from new foreign manufacturing firms in the Pearl River Delta. *Applied Geography*, 106, 11–21. <https://doi.org/10.1016/j.apgeog.2019.03.005>
- Ye, Y., Wu, K., Zhang, H., Wu, Q., & Chen, W. (2019b). Geographical agglomeration and location factors of the new-born cross-border manufacturing firms in the Pearl River Delta. *Progress in Geography*, 38(10), 1583–1595
- Yi, C., & Huang, Y. (2014). Housing Consumption and Housing Inequality in Chinese Cities During the First Decade of the Twenty-First Century. *Housing Studies*, 29(2), 291–311. <https://doi.org/10.1080/02673037.2014.851179>
- Zambrano-Monserrate, M. A., Alejandra Ruano, M. (2019) Does environmental noise affect housing rental prices in developing countries? Evidence from Ecuador. *Land Use Policy* 87 <https://doi.org/10.1016/j.landusepol.2019.104059>

- Zhang, S., Wang, L., & Lu, F. (2019). Exploring Housing Rent by Mixed Geographically Weighted Regression: A Case Study in Nanjing. *Isprs International Journal of Geo-Information*, 8(10). <https://doi.org/10.3390/ijgi8100431>
- Zhou, S., Deng, L., Kwan, M.-P., & Yan, R. (2015). Social and spatial differentiation of high and low income groups' out-of-home activities in Guangzhou, China. *Cities*, 45, 81–90. <https://doi.org/10.1016/j.cities.2015.03.002>

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Authors and Affiliations

Yang Wang^{1,2}  · Kangmin Wu^{1,2}  · Lixia Jin^{1,2} · Gengzhi Huang³ · Yuling Zhang¹ · Yongxian Su^{1,2} · Hong'ou Zhang¹ · Jing Qin^{4,5}

- ¹ Key Lab of Guangdong for Utilization of Remote Sensing and Geographical Information System, Guangdong Open Laboratory of Geospatial Information Technology and Application, Guangzhou Institute of Geography, Guangdong Academy of Sciences, Guangzhou 510070, China
- ² Southern Marine Science and Engineering Guangdong Laboratory (Guangzhou), Guangzhou 510070, China
- ³ School of Geography and Planning, Sun Yat-Sen University, Guangzhou 510275, China
- ⁴ School of Tourism Sciences, Beijing International Studies University, Beijing 100024, China
- ⁵ Research Center of Beijing Tourism Development, Beijing 100024, China