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SPATIAL HETEROGENEITY IN IMPLICIT HOUSING PRICES: EVIDENCE FROM HANGZHOU, CHINA

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ABSTRACT. Estimated coefficients in hedonic price models are generally assumed to be constant throughout the entire study area. However, increasing evidence reveals that the marginal prices of housing characteristics may vary over space and that the spatial heterogeneity problem in implicit housing prices should be given attention. Taking Hangzhou, China, as an example, this study uses the micro data of 603 residential communities in 2014 to examine spatial heterogeneity in implicit housing prices. On the basis of the traditional hedonic price model, we establish spatial expansion and geographically weighted regression (GWR) models for comparative analysis. Results show that the spatial expansion and GWR models have excellent goodness of fit and can improve the traditional hedonic price model. The mixed geographically weighted regression (MGWR) model further reveals that the implicit prices of nine housing characteristics vary significantly over space and that the impacts of the four remaining housing characteristics on housing prices are fixed throughout the entire study area. Unlike the traditional hedonic price model and spatial expansion model, the GWR/MGWR model has the unique advantage of visually providing the spatial distribution of implicit housing prices and accurately describing spatial heterogeneity.

KEYWORDS: Housing price; Spatial heterogeneity; Hedonic price model; Geographically weighted regression

1. INTRODUCTION

With the acceleration of China's urbanization process, the real estate market has developed rapidly across many cities. Along with the rapid development in Chinese housing market is the evident spatial differentiation of housing prices in some big cities, a topic that has attracted the attention of many scholars (Xu 1997; Wang, Zhu 2004; Zhou, Luo 2004; Zhou, Zhen 2008; Ma *et al.* 2008). Hangzhou, well known for the West Lake, is an important central city of the Yangtze River Delta in Eastern China. The property market in Hangzhou is characterized by high supply, high demand, and sustainably rising prices, thus giving birth to the "Hangzhou phenomenon", which is widely recognized by the academia and the real estate industry in China (Wen *et al.* 2014a). The residential market in Hangzhou has been ebullient during the last two decades, such that the average housing price once recorded 25840 RMB/m^2 in 2010 as the top one in China (Hui *et al.* 2016). The housing market of Hangzhou is typical in China, thus, the city represents a perfect context for investigating the spatial variation of housing price, which is a key issue worthy of study.

Currently, the hedonic price model is the main research method used to quantify the determinants of housing prices and to estimate the impacts of such determinants on housing prices. In the hedonic price model, the ordinary least squares (OLS) method is adopted to estimate the implicit prices of housing characteristics (Wang, Huang 2007; Hao, Chen 2007; Wen *et al.* 2010). However, overlooking the spatial fixity property of housing, the traditional hedonic price model assumes that housing prices are mutually independent in the spatial distribution. Such assumption may lead to bias in the model estimation results. As housing prices represent a type of spatial data, the topics of spatial dependence and heterogeneity have caught the attention of many scholars (Anselin 1988,

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2003; Dubin 1998; Páez *et al.* 2008; Bourassa *et al.* 2010). With the development of spatial econometrics, the spatial lag and spatial error models have been used to improve the hedonic price model, and deal with the spatial dependence problem (Anselin 1988; Osland 2010). However, the spatial lag and spatial error models still assume that the influence of housing characteristics is fixed throughout the entire market area and that implicit housing prices are spatially stationary in a city. Therefore, the problem of spatial heterogeneity remains unresolved.

Spatially varying coefficient models is proposed to deal with the problem of spatial heterogeneity. It mainly includes three methods: dummy variable method based on housing submarkets, spatial expansion model, and geographically weighted regression (GWR). The first method constructs the hedonic price model according to housing submarkets, or dummy variables are integrated in modeling spatial differences (Schnare, Struyk 1976; Quigley 1985; Michaels, Smith 1990; Goodman, Thibodeau 1998, 2003). Much of the literature considers submarkets as a priori given areas modeled by regional dummy variables. The data-driven approaches, such as principal component and cluster analysis (Bourassa *et al.* 1999; Helbich *et al.* 2013), fuzzy clustering algorithms (Hwang, Thill 2009; Helbich 2015) or neural networks (Kauko 2004), seem to be a rational option to define submarkets. Cassetti (1972) proposed a spatial expansion model that estimates implicit price with the addition of spatial location; the estimation is carried out by means of an interaction item between the variables of housing characteristics and location coordinates in the general model. If the interaction term is significant, then the implicit price of the corresponding housing characteristic has spatial heterogeneity (Can 1992). Meanwhile, GWR is a very effective method for identifying spatial nonstationarity; hence, it has been widely used in social and economic fields (Fotheringham *et al.* 1996, 2002). For example, Bitter *et al.* (2007) verified that GWR is better than the spatial expansion model in the aspects of explanatory power and predictive ability.

Therefore, this paper aims at understanding how the implicit value given to housing attributes may vary over space in the transitional China. We take Hangzhou, China as a case, set up a spatial expansion model and GWR model to optimize the traditional hedonic price model, and conduct an empirical analysis of the spatial heterogeneity of implicit housing prices. The paper also seeks to contribute to the existing literature in the following ways. First, we employ a data set pertaining to a Chinese housing market. Previous studies examine spatial variations of housing price in Western countries, such as Canada (Kestens *et al.* 2006), U.S. (Bitter *et al.* 2007), Austria (Helbich *et al.* 2014). However, no attempt has been made to show the empirical evidence of spatial heterogeneity in Hangzhou under the background of Chinese rapid urbanization. Second, our empirical study is carried out through comparing three methods: the traditional hedonic model, spatial expansion model, and GWR. The GWR has outperformed the other two models and provided more detailed results. Then, we improve the traditional GWR model and apply the MGWR model to account for the spatial effects of parameter estimates. Such a comparison adds to our understanding of the role that spatial heterogeneity plays in housing markets, and makes us obtain reliable results for modeling housing prices. In consequence, it is hoped that the results of this study will provide a reference for the similar studies in Chinese cities. The following research questions will be answered in this paper: (1) Does the spatial heterogeneity has emerged in the Hangzhou housing market? (2) Which implicit prices of housing attributes exist the spatial heterogeneity? (3) Do the spatial models outperform the traditional hedonic price model in capturing the spatial heterogeneity?

The structure of this paper is as follows. Section 2 presents a literature review, which summarizes the empirical progress of research methods related to spatial heterogeneity. Section 3 discusses the data sources, variable selection, and model specification. Section 4 reports the results and discusses the traditional hedonic price model, spatial expansion model, and GWR model. Section 5 concludes the paper.

2. LITERATURE REVIEW

Spatial heterogeneity occurs when activities or phenomena in a certain spatial location are different from those in other areas (Anselin 1988). Specifically, it means that a geographic region in a space lacks homogeneity. Spatial heterogeneity reflects the instability of the economic behavior relation between spatial observations in the economic practice. In the case of spatial heterogeneity within cross-sectional data, the impact of explanatory variables on different areas may vary when establishing an econometric model. Therefore, assuming that economic behavior is different over space is realistic. To deal with the spatial heterogeneity of the implicit price of housing characteristics, three main methods are employed: dummy variable method, spatial expansion method, and GWR.

2.1. Dummy variable method based on housing submarkets

The first method establishes the hedonic price model according to the concept of market segmentation or analyzes the spatial heterogeneity of implicit housing prices with dummy variables, such as direction and location variables. Goodman and Thibodeau (1998, 2003) defined the housing submarkets in Dallas, U.S., through the hierarchical method and summarized the spatial difference among the submarkets based on the quality of public education. Shi and Guo (2009) set up three models according to the direction from the Shanghai South Railway Station. The results show that the influence of the railway station on housing prices obviously varies in different directions. Li *et al.* (2010) found significant differences in the regression coefficients of the four submarkets, which prove that the implicit housing prices are heterogeneous in the Beijing housing market.

Some scholars have studied the spatial heterogeneity of implicit prices by incorporating dummy variables into the hedonic price model. Coulson (1991) considered the interaction between the direction dummy and distance variable to reflect direction heterogeneity but found that the housing price gradient has no significant change in the four directions. Söderberg and Janssen (2001) found that a significant negative relation exists between distance to CBD and housing price. When the direction variables are considered, the absolute value of the eastward gradient price is at a minimum, but the price gradients of south and west are insignificant. Zhang (2012) set eight direction dummy variables related to the three city centers in Hangzhou. A majority of the direction–distance interaction variables are significant, which indicates the implicit prices for the three CBDs have spatial heterogeneity.

In general, this method is easy to understand and operate. However, its limitation emerges in the division of the market subjectively. Submarkets are often difficult to divide, and summarizing the general rules of the housing market is problematic. In certain cases, the expected results are not achieved because a series of dummy variables must be increased during modeling. It might induce the modifiable areal unit problem, which can further result in biased estimates of the hedonic price function (Helbich *et al.* 2013). The focus on housing submarkets also posits that spatial heterogeneity is a discrete phenomenon and does not allow attribute prices to vary in a continuous manner over space (Bitter *et al.* 2007).

2.2. Spatial expansion model

The second method for dealing with the spatial heterogeneity of implicit housing prices is the spatial expansion model. Casetti (1972) first proposed the spatial expansion model and illustrated the application of an extended model. The expansion method is well suited to modeling complex spatial non-linear relationships because it lends itself to operationalize the integration of complex geographical contexts and non-spatial models. The spatial expansion model has received attention in the real estate context from Can (1992), Theriault *et al.* (2003), and Fik *et al.* (2003). For example, Theriault *et al.* (2003) set up an expansion model with the interaction between housing and neighborhood attributes and observed a significant improvement in the goodness of fit of the model. Fik *et al.* (2003) utilized a fully interactive model that includes higher-order polynomials. However, the study only considered three variables of housing characteristics; thus, distinguishing whether the spatial heterogeneity is derived from the intrinsic parameter variation or from the effects of the omitted variables is difficult. Given the difficulty in obtaining data, studies on the spatial expansion model are still comparatively limited in China. Dong *et al.* (2011) utilized the spatial expansion model to study the influencing factors of residential land price in Beijing based on micro data from 2004 to 2009.

The expansion method has an especially useful role in spatial modeling. Constructing a spatial expansion model does not require prior knowledge of the local housing market; only the collection of the geographic coordinates of all samples is necessary. Compared with the dummy variable method based on submarkets, the spatial expansion model minimizes the need to understand the local housing market when defining submarkets. It also provides great convenience for researchers who may not be familiar with the housing market. However, the expansion method has some limitations (Fotheringham, Brunsdon 1999; Fotheringham *et al.* 2002). The technique is dependent upon the complexity of the expansion equation to display trends in relationships over space. The form of the expansion equations needs to be assumed a priori although more flexible functional forms could be used, and the expansion equations must be assumed to be deterministic in order to remove problems of estimation in the terminal model. Clearly the maps of the spatially varying parameter estimates obtained through the expansion method might obscure important local variations to the broad trends represented by the expansion equations.

2.3. Geographically weighted regression model

The GWR model, proposed by Fotheringham *et al.* (1996), Fotheringham and Brunsdon (1998), is the third method for revealing spatial nonstationarity. GWR is based on the non-parametric technique of locally weighted regression developed in statistics for curve-fitting and smoothing applications. This method has been presented as a method to conduct inference on spatially varying relationships, in an attempt to extend the original emphasis on prediction to confirmatory analysis (Wheeler 2014). Some diagnostic tests in GWR have become more sophisticated, for instance, the development of formal test statistics for spatial nonstationarity and heterogeneity of the local model parameters (Leung *et al.* 2000a). Several hedonic studies emphasize the appealing empirical performance of GWR. As expected, Saefuddin and Yekti (2012), Hanink *et al.* (2012) and McCord *et al.* (2012) reported a better GWR performance compared to OLS. Kestens *et al.* (2006) and Bitter *et al.* (2007) measured GWR against the spatial expansion model, and verified that the GWR model outperforms the spatial expansion model in terms of explanatory power and predictive accuracy.

Generally, the GWR model assumes that all explanatory variables lead to significant changes in housing prices over space because the housing market is affected by government policies, socioeconomic relations, and so on. However, such assumption is not entirely consistent with reality. Therefore, Fotheringham *et al.* (2002) improved the original GWR model by proposing the MGWR model, which divides independent variables into global and local variables. The estimated coefficients of the MGWR model are fixed for global variables, which relate to the homogeneous influence of explanatory variables on housing prices over space, while the coefficients of local variables change with spatial position. Compared with the OLS and GWR models, the MGWR model can accurately determine the nonstationarity of spatial data and reveal the spatial distribution of local variables. Helbich *et al.* (2014) constructed the MGWR model with the housing data in Austria and found that the spatial heterogeneity of implicit prices is more complex than other factors that can be modeled by regional indicators or purely local models. They verified that both stationary and nonstationary effects exist in the same housing market.

The GWR model has its individual advantages in the analysis of spatial heterogeneity. First, this method is appealing because it allows spatially varying parameters in the analysis of implicit housing prices. The GWR model also performs better than the OLS model and the spatial expansion model in terms of explanatory power and prediction ability. Second, The GWR model can provide detailed parameters of each sample point and visualize the spatial pattern of the housing market using geographic information system (GIS) software, which could reveal the spatial difference of implicit prices intuitively and clearly. However, the GWR model possesses the following limitations (Wheeler, Tiefelsdorf 2005; Helbich 2015). First, a number of data points are repeatedly used in parameter estimations, and a strong correlation between the GWR parameters might be present. Second, the potential repercussions of multicollinearity in GWR require a careful application of the technique and the use of diagnostic tools. The local multicollinearity can falsely induce parameter variability and inflates parameter variance. Finally, the resulting standard errors are just approximations, and the classical statistical test procedures are pseudo counterparts of the traditional test procedures.

3. DATA AND MODELS

3.1. Data source

Hangzhou, the capital of the Zhejiang Province in China, is an important central city of the Yangtze River Delta. It's located at the southeast coast of China, and northeast of Zhejiang Province, with only 180 kilometers from Shanghai, the largest city in China. Hangzhou is a famous city in history and culture and also an important national tourist city. The city is well known for its picturesque natural landscape and environment – 65.6% of its land area is hilly and mountainous (with an elevation range between 200 and 1,100 meters) concentrated in the west, middle and south, and 26.4% of its land area plain (with a surface elevation range between 2 to 10 meters) in its northeast, leaving 8% of the area water bodies (Qian 2015). The world's longest artificial cannel named the Great Cannel and the Qiantang River with the magnificent view of tidal bore are passing through the city. Hangzhou serves as the political, economic, scientific, educational, information, cultural, and tourism center of the Zhejiang Province. The main city of Hangzhou is made up of the Shangcheng, Xiacheng, Gongshu, Jianggan, Binjiang, and Xihu districts and has a total area of 167.01 km^2. This paper examines the entire developed area of Hangzhou, which comprises the urban area of the six districts.

We select gated communities as the basic analysis unit. Our sample data contain 660 communities distributed within six urban districts. The housing data for April 2014 are obtained from real estate agent companies in Hangzhou. Considering the short time span covered by the data, we ignore the effect of time on price. We also conduct a field survey on the housing communities in the study area to confirm and supplement the related data (e.g., the interior environment of the communities, property management quality, surrounding environment, and living facilities of the communities) that are not provided by the real estate companies and to enhance the completeness and accuracy of our data.

The GIS provided by the Sogou Map Company is used to measure three location characteristic variables. We use the map to obtain the walking distances from the community to the traditional CBD (Wulin Square), the new CBD (Qianjiang New Center) of Hangzhou, and the West Lake. Before the model estimation, the data are preprocessed to exclude abnormal values, resulting in effective samples of 603 communities.

3.2. Variable description

We use the average housing price (*P*) from the community level as the dependent variable of the hedonic price model. Following the framework of the hedonic price analysis, we choose independent variables from structural, neighborhood, and location characteristics. One structure characteristic, nine neighborhood characteristics, and three location characteristics are used as alternative variables for the modeling. Table 1 shows the variable measurements and expected signs.

Table 1. Variable definitions and expected signs

Variable	Variable definition and measuring methods	Expected sign
Building age	Building age (year; the age of a housing built in 2014 is 1)	–
Inner environment	Environment quality inside the community; divided into five degrees: quite bad (scored 1), bad (scored 2), common (scored 3), good (scored 4), very good (scored 5)	+
External environment	Natural environment quality around the community; divided into five degrees: quite bad (scored 1), bad (scored 2), common (scored 3), good (scored 4), very good (scored 5)	+
Property management	Service quality of community property management; divided into five classes: quite bad (scored 1), bad (scored 2), common (scored 3), good (scored 4), very good (scored 5)	+
Sports facility	General quality of community sports facilities inside the community; divided into five classes: quite bad (scored 1), bad (scored 2), common (scored 3), good (scored 4), very good (scored 5)	+
Nearby university	Dummy variables: college or university within 1,000 m (evaluated as 1; 0 otherwise)	+
Living facility	Supermarket, terminal market, bank, post office, hospital within 1,000 m from the community; each item scored with 1 (total is 5)	+
Education facility	Kindergarten, elementary school, junior high school, high school within 1,000 m from the community; each item scored with 1 (total is 4)	+
Nearby subway	Dummy variables: metro stations within 500 m from the community(evaluated as 1; 0 otherwise)	?
Traffic condition	Total number of bus routes within 1,000 m of the community	+
Distance to Wulin Square	Walking distance from the community to Wulin Square (km)	–
Distance to the West Lake	Walking distance from the community to the West Lake (km)	–
Distance to the Qianjiang New Center	Walking distance from the community to the Qianjiang New Center (km)	–

3.3. Model specification

Four kinds of functional forms are commonly used in the hedonic price model: linear, logarithmic, semi-logarithmic, and logarithmic linear forms. Among the 13 independent variables in this study, four continuous variables (distance to Wulin Square, distance to the Qianjiang New Center, distance to the West Lake, and building age) could be considered to have a logarithmic form. After a series of trials, we find that for the same variables and sample data, models with a logarithmic form have relatively high explanatory powers. Model 1 is the traditional hedonic price model, which is defined in this paper as follows:

$$\ln P_i = \beta_0 + \sum_{j=1}^{13} \beta_j X_{ij} + \varepsilon_i , \qquad (1)$$

where: P_i is the average housing price for the community i; β_0, and β_j are the coefficients for estimation; and ε_i is the error term. X_{ij} represents the j^{th} average housing characteristic for the community i. Four continuous characteristic variables are applied in logarithmic form, and the dummy and class variables are applied in linear form.

To verify the existence of spatial heterogeneity, we construct two spatial expansion models based on the traditional hedonic price model while allowing the marginal price of the housing attributes to vary over space.

$$\ln P_i = \beta_0 + \sum_{j=1}^{13} \beta_j X_{ij} + \sum_{j=1}^{13} \beta_j u_i X_{ij} + \sum_{j=1}^{13} \beta_j v_i X_{ij} + \varepsilon_i ; \qquad (2)$$

$$\begin{aligned} \ln P_i = \beta_0 &+ \sum_{j=1}^{13} \beta_j X_{ij} + \sum_{j=1}^{13} \beta_j u_i X_{ij} + \sum_{j=1}^{13} \beta_j v_i X_{ij} + \\ &\sum_{j=1}^{13} \beta_j u_i u_i X_{ij} + \sum_{j=1}^{13} \beta_j v_i v_i X_{ij} + \sum_{j=1}^{13} \beta_j u_i v_i X_{ij} + \varepsilon_i \end{aligned} \quad ,(3)$$

where: u_i and v_i are the geographic Cartesian coordinates of the community i (we take the traditional city centre, the Wulin Square, as the origin, and the measurement unit is kilometer); P_i is the housing price; X_{ij} represents the j^{th} independent variable in location i; β_0 represents the constant term, and β_j denotes the regression coefficient of the j^{th} variable; ε_i is the random error.

Model 2 is the one-degree spatial expansion model that includes 13 housing characteristic variables that interact with the transverse and longitudinal coordinates, as shown in expression (2). Model 3 is the quadratic spatial expansion model in the form of a two-degree polynomial expansion of the coordinates. As a result, Model 3 yields 39 new independent variables in addition to the 26 variables included in Model 2. To avoid the collinearity problem, we restrict the spatial expansion model to the second order.

Model 4 is the GWR given the assumption that the regression coefficient is a function of the observation location. This model includes the same 13 housing characteristics used as independent variables in Model 1. The model specification is as follows:

$$\ln P_i = \beta_0 (u_i, v_i) + \sum_{j=1}^{13} \beta_j (u_i, v_i) X_{ij} + \varepsilon_i , \qquad (4)$$

where: P_i is the housing price; X_{ij} represents the j^{th} independent variable; $\beta_j(u_i, v_i)$ is the regression coefficient for variable j at regression point i; u_i and v_i are the geographic coordinates of the i^{th} community.

Similar to Ordinary Least Squares, the vector of estimated regression coefficients at one location is

$$\beta\ (u_i, v_i) = \left[X^T W(u_i, v_i) X \right]^{-1} X^T W(u_i, v_i) P , \quad (5)$$

where: X is the design matrix of covariates and leading column of ones for the intercept; P is the $n\times1$ vector of the housing price in logarithmic form; $W(u_i, v_i) = diag\left[w_1(u_i, v_i) \quad w_2(u_i, v_i) \quad \dots \quad w_n(u_i, v_i) \right]$ is the $n\times n$ diagonal weights matrix calculated for each location i. The weight matrix W must be calculated at each location using the kernel function and bandwidth before the local regression coefficients can be estimated. Given the definition of the estimated regression coefficients, GWR can be viewed as a locally weighted least squares regression model where the weights associate pairs of data points.

Model 5 is the MGWR, which includes the global variables fixed in the entire study area and the local variables that vary over space. The functional form is defined as follows:

$$\ln P_i = \sum_{j=0}^{q} \beta_j X_{ij} + \sum_{j=q+1}^{13} \beta_j (u_i, v_i) X_{ij} + \varepsilon_i , \qquad (6)$$

where: β_j is the parameter for estimation that corresponds to the global variable j in the model; $\beta_j(u_i, v_i)$ represents the regression coefficient for local variable j at regression point i, it is the function of the geographic location coordinates (u_i, v_i). The MGWR estimation procedure can be achieved by a multistep algorithm, a two-step procedure and a constrained type (Fotheringham *et al.* 2002; Wei, Qi 2012). Following the suggestion of Helbich *et al.* (2013), the multistep algorithm is applied in this study for its easier implementation.

In the empirical estimation of the GWR/MGWR model, a spatial weight matrix needs to be introduced. The spatial weight function can be determined in several ways, such as through the threshold distance, inverse distance, bi-square function and Gaussian function. The results of GWR are sensitive to the choice of bandwidth. Besides assuming a predefined and fixed bandwidth, an adaptive bandwidth has been proven to be highly suitable in practice (McMillen, Redfearn 2010). Therefore, we chose a Gaussian function as an adaptive spatial kernel that allows the bandwidth to vary based on the density of house sales around each regression point, thus encapsulating a smaller area where data are rich and a larger area where data are sparse. To obtain the optimal bandwidth, Fotheringham *et al.* (2002) proposed that the GWR model has the best bandwidth when the value of the corrected Akaike Information Criterion (AICc) or the cross-validation (CV) is at the minimum.

Table 2. Regression results of the traditional hedonic price model

Variables	Coefficients	*t*
Constant	10.188***	117.612
ln(building age)	−0.011	−0.734
Inner environment	0.013	1.221
External environment	0.008	0.809
Property management	0.042***	5.328
Sports facility	0.031***	3.925
Nearby university	0.046***	2.979
Living facility	0.018**	2.208
Education facility	0.033***	3.390
Nearby subway	0.020	1.162
Traffic condition	−0.002***	−3.023
ln(distance to Wulin Square)	−0.067***	−3.429
ln(distance to the West Lake)	−0.221***	−12.694
ln(distance to the Qianjiang New Center)	−0.059***	−4.018
AICc	−468.846	
Adjusted R^2	0.567	

Note: ***,**, and * represent significance at the 1%, 5%, and 10% levels, respectively.

4. RESULTS AND DISCUSSION

4.1. Traditional hedonic price model

As the traditional hedonic price model, Model 1 is estimated by the OLS method. The regression results are shown in Table 2. The analysis of variance results of the model show that the significant probabilities for the F value are less than 0.001, which confirms the validity of the equation and rejects the original hypothesis of all coefficients being zero. The value of the adjusted R^2 is 0.567, which means that the independent variables can explain 56.7% of the variation of the dependent variable. The values of the variance inflation factor of all variables are between 1.272 and 4.203, which shows that the degree of collinearity among the independent variables is not serious.

Model 1 is a global model in which the implicit prices are held unchanged throughout the study area. Nine housing characteristic variables significantly affect the housing price. Except for traffic condition, the other coefficients exhibit signs that match the theoretical expectations. The implicit price of traffic condition is negative, probably because private car ownership has grown rapidly during the rapid economic development period in Hangzhou and has thus reduced the dependence on public transport such as buses. The presence of buses around the residential area inevitably brings about some negative effects, such as traffic congestion, exhaust pollution, and noise pollution. Hence, bus lines are likely to have a negative effect on housing price. The results are substantially consistent with the findings of Wu *et al.* (2008) and Wen *et al.* (2014b), Wen and Tao (2015).

The regression coefficient of the nearby subway variable does not pass the significance level of 10%, which indicates that the subway has no significant influence on housing price in the traditional hedonic price model. However, from a theoretical point of view, subways should have a significant impact at least on the surrounding housing prices. As the traditional hedonic price model can estimate only the average implicit price, the regression coefficient of the nearby subway variable ultimately fails to reach the 10% significance level. Similarly, the building age variable in the traditional hedonic price model is not significant. Furthermore, the statistics of Moran's I for the spatial autocorrelation test is 0.387, and the significance level is below 0.001. These results show the obvious spatial effect of housing price on the regional distribution in Hangzhou, indicating that OLS parameter estimates are inefficient and t-ratios are biased (Dubin 2003). Therefore, We use the spatial extension and GWR models for further analysis.

4.2. Spatial expansion model

With the interaction terms between the 13 variables and the coordinates of the sample points, two spatial expansion models are estimated by OLS.

Table 3. Regression results of spatial expansion models

Variables	One-degree term model		Quadratic term model	
	Coefficients	t	Coefficients	t
Constant	10.698 ***	91.871	10.699 ***	67.515
ln(building age)	−0.061 ***	−3.765	−0.079 ***	−3.247
Inner environment	0.022 *	1.649	0.029 ***	1.729
U(inner environment)			0.008 *	1.803
External environment	0.022 *	1.653	0.050 ***	2.616
U(external environment)			−0.015 **	−2.526
Property management	0.036 ***	3.490	0.033 **	2.267
V^2(property management)			−0.001 *	−1.718
Sports facility	0.032 ***	4.034	0.055 ***	4.131
V^2(sports facility)			−0.001 *	−1.877
V(nearby university)	0.007 *	1.792		
Living facility	0.032 ***	3.043		
U(living facility)	−0.007 **	−2.445	−0.010 **	−1.984
Education facility			0.050 **	2.461
U^2(education facility)			−0.003 **	−2.471
Nearby subway			−0.209 ***	−3.208
U(nearby subway)			0.053 ***	2.587
V(nearby subway)	0.018 **	2.387	0.081 ***	3.232
UV(nearby subway)			−0.013 **	−2.493
Traffic condition	−0.005 ***	−3.585	−0.004 **	−2.037
U(traffic condition)	0.001 *	1.818		
V(traffic condition)	0.001 ***	3.682	0.001 *	1.952
ln(distance to the Wulin Square)	−0.087 *	1.786	−0.168 **	−2.149
Uln(distance to Wulin Square)	0.033 **	2.212	0.128 ***	3.099
Vln(distance to Wulin Square)	0.019 *	1.898		
U^2ln(distance to Wulin Square)			−0.021 **	−2.547
ln(distance to the West Lake)	−0.269 ***	−7.596	−0.336 ***	−6.557
Vln(distance to the West Lake)	−0.022 **	−2.413		
V^2ln(distance to the West Lake)			−0.008 *	−1.648
ln(distance to the Qianjiang New Center)	−0.185 ***	−4.028	−0.237 ***	−3.061
Uln(Distance to the Qianjiang New Center)	−0.015 *	−1.716	−0.076 **	−2.505
U^2ln(distance to the Qianjiang New Center)			0.017 ***	3.134
AICc	−605.089		−657.128	
Adjusted R^2	0.671		0.704	

Note: ***,**, and * represent significance at the 1%, 5%, and 10% levels, respectively.

The values of the variance inflation factor of all variables are less than 10, which show that the serious collinearity is not present in the two expansion models. We report only the coefficients that are at least significant at the 10% level.

The results for Model 2, the one-degree spatial expansion, are shown in the second and third columns. The adjusted R^2 is 0.671, which indicates that Model 2 can more effectively explain the variations of the dependent variable and demonstrate a more favorable goodness of fit compared with Model 1. Ten "base" housing characteristic variables have significant effects on housing prices, and five of these variables interact with location coordinates. Ten location–characteristic interaction terms are significant at the 10% level, which indicates that spatial heterogeneity exists in the marginal prices of these housing characteristics. For example, the regression coefficients of Living facility is 0.032 which indicate that, in general, the value of Living facility increases by 1 unit and the housing prices will increase by 3.2%. The interaction term of U(living facility) is −0.007, which reveal that spatial heterogeneity exists in the horizontal direction, and for the same quality of living facility, an additional 1 km from the Wulin Square (measured horizontally) will reduce an average community housing price by 0.7%.

Five variables, namely, building age, inner environment, external environment, property management, and sports facility, have significant effects on housing prices, but their interaction terms are not significant. This condition indicates that the marginal prices of these variables do not vary in the locational context. Furthermore, two variables, namely, nearby university and nearby subway, are not significant. However, their interaction terms are significant at the 10% and 5% significance levels, respectively, indicating that the interaction terms still have space differences to some extent.

Table 3 also reports the results of Model 3, the quadratic spatial expansion model. The addition of the quadratic interaction terms in Model 3 results in an improvement in the explanatory power as the adjusted R^2 increases from 0.671 to 0.704. A total of 15 out of the 65 interaction variables are significantly different from 0 at the 10% significance level. The one-degree interaction terms of four variables and the quadratic interaction terms of seven variables have significant effects on the housing prices. This result provides strong evidence of implicit prices with complicated spatial distribution patterns.

The results of the two spatial expansion models confirm that spatial heterogeneity exists in the implicit prices of the housing characteristics of the Hangzhou market. For example, the variables of inner environment, external environment, nearby subway, and building age are insignificant in the traditional hedonic price model, but their interaction terms are significant in Models 2 and 3. This result indicates the influence of the four variables on housing price and their tendency to still change over space. No significant residual dependence on a 0.01 level is detected by the Moran's I, which indicates spatial expansion models can capture the spatial effect and be used to improving the misspecification problem, which lead to inefficient parameter estimations in the traditional hedonic price model.

4.3. Geographically weighted regression model

With a Gaussian kernel, CV determines an optimal adaptive bandwidth that includes 182 observations. Sensitivity analysis with alternative kernels (i.e. bi-square kernel) shows no significant differences. The values of VIF of all variables are less than 5, which do not suggest a problem of collinearity among the independent variables. Table 4 shows the regression results of Model 4 (GWR). The adjusted R^2 is 0.757, which is significantly better than that in the traditional hedonic price model and the two spatial expansion models. This improvement reflects that the GWR model can effectively explain the relationship between housing prices and the explanatory variables and provide strong evidence that spatial heterogeneity plays an important role in the Hangzhou housing market. The GWR parameter estimates, which vary at each observation point, are described by their minimum, median, and maximum values, as well as by their interquartile range.

For example, the lower quartile of the regression coefficients of the distance to the West Lake is −0.421 and the upper quartile is −0.171. These values indicate that in a certain space location, the distance to the West Lake increases by 1% and the housing prices decline by 0.421%. Meanwhile, in another space location, the distance to the West Lake increases by 1% while the housing prices decline by 0.171%. The magnitude of change is 0.25%. One advantage of GWR is that the spatial patterns of the parameter estimates can be easily mapped and visualized. Figure 1 reveals the spatial effect of the distance to the West Lake on housing price. Almost all samples reach the significance level of 1% by P value. Hence, the distance to the West Lake has an important influence on the housing prices throughout the entire study area. As expected, the estimates are negative and exhibit localized spatial patterns. The highest estimates are found within North Hangzhou, where the housing prices are relatively lower than that in other areas, resulting in the rapid decrease of the price gradient of the distance to the West Lake. The estimates are the smallest and exhibit

Table 4. Results of GWR model

Variables	Min	Lwr Quartile	Median	Upr Quartile	Max
Constant	5.373	9.804	10.520***	10.848	12.687
ln(building age)	−0.180	−0.107	−0.061**	−0.024	0.006
Inner environment	−0.034	0.029	0.043**	0.066	0.097
External environment	−0.042	−0.005	0.015*	0.028	0.103
Property management	−0.015	0.006	0.016***	0.026	0.051
Sports facility	−0.019	0.015	0.028***	0.043	0.076
Nearby university	−0.104	−0.015	0.015***	0.050	0.210
Living facility	−0.087	−0.017	0.012***	0.047	0.092
Education facility	−0.068	−0.015	0.010***	0.047	0.155
Nearby subway	−0.170	−0.004	0.021**	0.048	0.164
Traffic condition	−0.009	−0.004	−0.002***	0.000	0.005
ln(distance to Wulin Square)	−1.295	−0.151	−0.034***	0.124	1.159
ln(distance to the West Lake)	−1.224	−0.421	−0.280***	−0.171	0.083
ln(distance to the Qianjiang New Center)	−1.317	−0.272	−0.131***	0.082	2.775
AICc	−714.328				
Adjusted R^2	0.757				

Note: ***,**, and * represent significance at the 1%, 5%, and 10% levels, respectively.

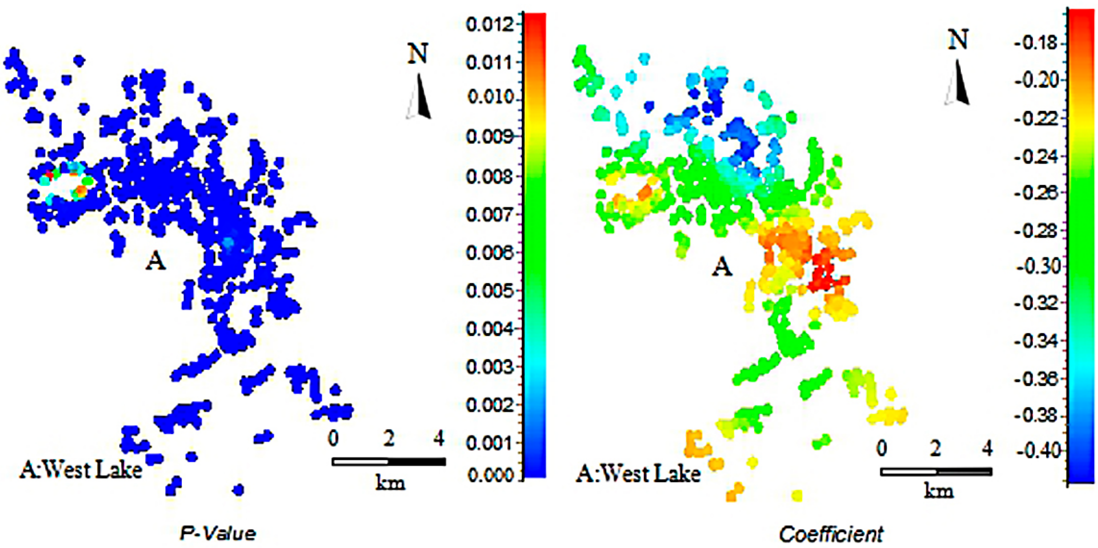

Fig. 1. *P* value and regression coefficients for the distance to the West Lake variable

relatively smooth spatial trends within Central Hangzhou (the eastern region of the West Lake), which belongs to the traditional downtown area with convenient public facilities. The housing prices in this area are relatively high. In other words, the GWR model shows that the implicit prices of 13 housing characteristics are not entirely fixed in space but exist with spatial heterogeneity. These results verify that the global/average estimation by the traditional hedonic price model may be flawed.

Model 5 is the MGWR. Compared with the GWR model, the MGWR model divides independent variables into two types: global variables with fixed estimated coefficients (see Table 5) and local variables that change over space (see Table 6). Following the test statistic of Leung *et al.* (2000a), we find that four independent variables in the study are global variables while the remaining nine variables are local variables. Again, applying a Gaussian kernel function, CV results in an opti-

Table 5. Regression results for global variables

Variables	Coefficients	*t* value	Critical value (10%)	Critical value (5%)
Inner environment	0.048	4.176	1.648	1.965
Nearby university	0.040	2.635		
Sports facility	0.021	3.246		
Property management	0.012	1.722		

Table 6. Regression results for local variables

Variables	Min	Lwr Quartile	Median	Upr Quartile	Max
Constant	3.401	9.887	10.354	10.879	13.094
ln(building age)	−0.214	−0.113	−0.079	−0.030	0.033
External environment	−0.055	−0.006	0.015	0.031	0.109
Living facility	−0.107	−0.016	0.011	0.051	0.105
Education facility	−0.094	−0.015	0.025	0.045	0.194
Nearby subway	−0.205	−0.013	0.007	0.042	0.254
Traffic condition	−0.011	−0.004	−0.002	0.000	0.005
ln(distance to Wulin Square)	−1.739	−0.160	−0.003	0.120	1.515
ln(distance to the West Lake)	−1.328	−0.403	−0.307	−0.142	0.142
ln(distance to Qianjiang New Center)	−1.594	−0.279	−0.069	0.072	3.862
AICc	−756.902				
Adjusted R^2	0.766				

mal bandwidth of 168 observations for the MGWR. The F(3)-test (Leung *et al.* 2000a) confirms that all spatially varying variables are statistically significant. No significant residual dependence on a 0.01 level is detected by the Moran's I (Leung *et al.* 2000b).

The global variables of inner environment, nearby university, sports facility, and property management, as well as their t values, are higher than the corresponding critical value of the 10% significance level. This result indicates that these four housing characteristics have significant impacts on housing prices but that their implicit prices are constant throughout the study area. In addition, spatial heterogeneity obviously does not exist. The other nine local variables, with widely varying parameter estimates over space, reflect complex, localized spatial patterns. For example, the nearby subway variable is not significant in the traditional hedonic price model. However, its average effect on housing prices is 0.7% in the MGWR model, and the lower and upper quartiles are −0.013 and 0.042, respectively. Evidently, the influence of this variable is changed in different spatial locations. After further investigation using the GWR software, only 32% of the sample points (along the subway) are found significant at the 5% level. Therefore, the implicit price of this variable is not significant in the global model.

The median values of the GWR/MGWR estimates show that all independent variables have plausible signs, however, the minimum and maximum values are extreme or counter intuitive in some cases. Farber and Yeates (2006) and Bitter *et al.* (2007) found similar results for several variables in their study. For example, the max.value for building age is 0.033 in MGWR, which may be because the building age is very old and the corresponding communities have historical value, therefore, the building age has a positive effect on housing prices at some regression points. Negative values for the coefficients of External environment, Living facility and Education facility, and positive values for coefficients of three location variables, are counterintuitive, however, such estimates are statistically significant within only a very small portion of the study area.

The adjusted R^2 value of the MGWR model is slightly higher than that of the GWR model at 0.766, which indicates that the MGWR model can explain 76.6% of the variations of the dependent variable. To evaluate the prediction accuracy of the spatial expansion and GWR models, we compare the absolute values of the residual errors. Among the samples with small errors, the spatial expansion models account for 43.9% while the GWR models (including MGWR) account for 56.1%; the prediction accuracy of the GWR models is clearly superior. The MGWR model has smaller errors in 50.1% of all samples than the GWR model. This result indicates that the prediction accuracies of the two models do not differ and that the MGWR model has no obvious advantage.

5. CONCLUSIONS

In this study, we collected data on 603 residential communities in six main districts of Hangzhou and established the traditional hedonic price model, spatial expansion model, and GWR model to test the spatial heterogeneity of the implicit price of housing characteristics. This study obtained the following findings:

(1) The models considering spatial heterogeneity have a better goodness of fit than the traditional hedonic price model. This finding is consistent with that of Bitter *et al.* (2007). The indicators adjusted R^2 and AICc show that the explanatory powers of the traditional hedonic price model, spatial expansion model, and GWR model progressively increase. Specifically, the adjusted R^2 of the traditional hedonic price model is only 0.567; those of the extended spatial models with one degree and quadratic terms are 0.671 and 0.704, respectively, which are more than ten percentage points higher than that of the traditional model. Meanwhile, the adjusted R^2 of the GWR model is 0.757. Compared with previous studies by Bitter *et al.* (2007), Saefuddin and Yekti (2012), Hanink *et al.* (2012), and McCord *et al.* (2012) which assume that all variables have non-stationary effects on house prices, this study proposes the MGWR model dealing with both stationary and non-stationary effects simultaneously. The performance of the MGWR model is the best but is only slightly higher than the GWR model. Therefore, the estimation results of the spatial expansion model and the GWR model are better than those of the traditional hedonic price model. The GWR/MGWR model in particular proves to be preferable in obtaining accurate predictions.

(2) The impacts of housing characteristics on housing prices are spatially heterogeneous. Both the spatial expansion model and the GWR model provide strong evidence that the implicit prices of key housing characteristics are not constant throughout the Hangzhou housing market but vary over space. The GWR model has a unique advantage in the spatial expression for implicit

prices. Compared with the traditional hedonic price model, the spatial expansion model considers interaction terms between housing characteristics and geographical coordinates and easily verifies spatial heterogeneity. However, it cannot analyze the spatial distribution pattern for implicit prices exactly. By allowing explicit parameter estimates to vary over space, the GWR model can obtain the implicit price of each sample point directly and provide the spatial distribution of housing implicit prices visually.

(3) Compared with the global models, MGWR is evidently more flexible, while being more parsimonious than GWR, which improves model efficiency (Wei, Qi 2012). The findings cohere with those of Helbich *et al.* (2013) and signify the importance of localised spatial effects on the marginal housing price. The results of the MGWR model further suggest that the implicit prices of building age, external environment, living facility, education facility, nearby subway, traffic condition, distance to Wulin Square, distance to the West Lake, and distance to the Qianjiang New Center are spatially heterogeneous. The impacts of these nine housing characteristics on housing prices vary significantly in the locational context, and the impacts on housing prices by the inner environment, nearby university, sports facility, and property management are relatively stable over space. Therefore, some deviation may exist between the estimated results and the actual situation when using the traditional hedonic price model, which assumes that all the implicit prices of housing characteristics are fixed throughout the entire study area. By dividing all the variables into global and local variables, the MGWR model performs better than the GWR model and achieves results that are close to reality.

It is important to emphasize some study limitations. Due to the existing data set at the community level, the total number of observations in this study is only 603. Model 3 has 78 independent variables, which may lead to the problem of small sample size. Although the final model includes 26 significant variables using the step-wise regression, it might be worth examining more observations, for example, increasing the time-series data, to make the results more convincing. Though GWR has been applied widely in diverse fields, the use of GWR for inferential analysis has been questioned and criticized (Wheeler, Tiefelsdorf 2005). The counterintuitive GWR estimates found at some locations in this study deserve further attention as well. The more complex approach of Bayesian spatially varying coefficient models has been demonstrated to better capture spatial nonstationarity in regression coefficients than GWR and is recommended as an alternative for inferential analysis (Gelfand *et al.* 2003; Wheeler, Calder 2007; Wheeler *et al.* 2014). Therefore, an important direction to extend the research in this paper is to use Bayesian models to estimate spatially varying regression coefficients as an alternative approach to GWR.

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REFERENCES

Anselin, L. 1988. *Spatial econometrics: methods and models*. Boston: Kluwer Academic. https://doi.org/10.1007/978–94–015–7799–1

Anselin, L. 2003. Spatial externalities and spatial econometrics, *International Regional Science Review* 26(2): 153–166. https://doi.org/10.1177/0160017602250972

Bitter, C.; Mulligan, G. F.; Dallerba, 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: 7–27. https://doi.org/10.1007/s10109–006–0028–7

Bourassa, S. C.; Hamelink, F.; Hoesli, M.; MacGregor, B. 1999. Defining housing submarkets, *Journal of Housing Economics* 8: 160–183. https://doi.org/10.1006/jhec.1999.0246

Bourassa, S.; Cantoni, E.; Hoesli, M. 2010. Predicting house prices with spatial dependence: a comparison of alternative methods, *Journal of Real Estate Research* 32(2): 139–160.

Can, A. 1992. Specification and estimation of hedonic housing price models, *Regional Science and Urban Economics* 22(3): 453–474. https://doi.org/10.1016/0166–0462(92)90039–4

Casetti, E. 1972. Generating models by the expansion method: applications to geographical research, *Geographical Analysis* 4: 81–91. https://doi.org/10.1111/j.1538–4632.1972.tb00458.x

Coulson, N. E. 1991. Really usefully tests of monocentric model, *Land Economics* 67(3): 299–307. https://doi.org/10.2307/3146425

Dong, G. P.; Zhang, W. Z.; Wu, W. J.; Guo, T. Y. 2011. Simulation and prediction of spatial heterogeneity in Beijing residential market, *Acta Geographica Sinica* 66(6): 750–760.

Dubin, R. 1998. Spatial autocorrelation: a primer, *Journal of Housing Economics* 7(4): 304–327. https://doi.org/10.1006/jhec.1998.0236

Dubin, R. 2003. Robustness of spatial autocorrelation specifications: some Monte Carlo evidence, *Journal of Regional Science* 43(2): 221–248. https://doi.org/10.1111/1467–9787.00297

Farber, S.; Yeates, M. 2006. A comparison of localized regression models in a hedonic house price context, *Canadian Journal of Regional Science* 29(3): 405–420.

Fik, T.; Ling, D.; Mulligan, G. 2003. Modeling spatial variation in housing prices: a variable interaction approach, *Real Estate Economics* 31(4): 623–646. https://doi.org/10.1046/j.1080–8620.2003.00079.x

Fotheringham, A. S.; Brunsdon, C. 1998. Geographically weighted regression: a natural evolution of the expansion method for spatial data analysis, *Environment and Planning A* 30(11): 1905–1927. https://doi.org/10.1068/a301905

Fotheringham, A. S.; Brunsdon, C. 1999. Local forms of spatial analysis, *Geographical Analysis* 31(4): 340–358. https://doi.org/10.1111/j.1538–4632.1999.tb00989.x

Fotheringham, A. S.; Brunsdon, C.; Charlton, M. 2002. *Geographically weighted regression: the analysis of spatially varying relationships*. Chichester: Wiley.

Fotheringham, A. S.; Charlton, M.; Brunsdon, C. 1996. Geographically weighted regression: a method for exploring spatial nonstationarity, *Geographical Analysis* (28): 281–298.

Gelfand, A. E.; Kim, H. J.; Sirmans, C. F.; Banerjee, S. 2003. Spatial modeling with spatially varying coefficient processes, *Journal of the American Statistical Association* 98(462): 387–396. https://doi.org/10.1198/016214503000170

Goodman, A. C.; Thibodeau, T. G. 1998. Housing market segmentation, *Journal of Housing Economics* 7(2): 121–143. https://doi.org/10.1006/jhec.1998.0229

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

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: 347–363. https://doi.org/10.1007/s11146–010–9262–3

Hao, Q. J.; Chen, J. 2007. Distance to CBD, transportation accessibility and the spatial differences of residential housing prices in Shanghai, *World Economic Papers* (1): 22–35.

Helbich, M. 2015. Do suburban areas impact house prices?, *Environment and Planning B-Planning & Design* 42: 431–449. https://doi.org/10.1068/b120023p

Helbich, M.; Brunauer, W.; Hagenauer, J.; Leitner, M. 2013. Data-driven regionalization of housing markets, *Annals of the Association of American Geographers* 103(4): 871–889. https://doi.org/10.1080/00045608.2012.707587

Helbich, M.; Brunauer, W.; Vaz, E.; Nijkamp, P. 2014. Spatial heterogeneity in hedonic house price models: the case of Austria, *Urban Studies* 51(2): 390–411. https://doi.org/10.1177/0042098013492234

Hui, E. C. M.; Liang, C.; Wang, Z.; Wang, Y. 2016. The roles of developer's status and competitive intensity in presale pricing in a residential market: a study of the spatio-temporal model in Hangzhou, China, *Urban Studies* 53(6): 1203–1224. https://doi.org/10.1177/0042098015572317

Hwang, S.; Thill, S.-C. 2009. Delineating urban housing submarkets with fuzzy clustering, *Environment and Planning B-Planning & Design* 36(5): 865–882. https://doi.org/10.1068/b34111t

Kauko, T. 2004. A comparative perspective on urban spatial housing market structure: Some more evidence of local sub-markets based on a neural network classification of Amsterdam, *Urban Studies* 41(13): 2555–2579. https://doi.org/10.1080/0042098042000294565

Kestens, Y.; Thériault, M.; Des Rosiers, F. 2006. Heterogeneity in hedonic modelling of house prices: looking at buyers' household profiles, *Journal of Geographical Systems* 8(1): 61–96. https://doi.org/10.1007/s10109–005–0011–8

Leung, Y.; Mei, C.-L.; Zhang, W.-X. 2000a. Statistical tests for spatial non-stationarity based on the geographically weighted regression model, *Environment and Planning A* 32: 9–32. https://doi.org/10.1068/a3162

Leung, Y.; Mei, C.-L.; Zhang, W.-X. 2000b. Testing for spatial autocorrelation among the residuals of the geographically weighted regression, *Environment and Planning A* 32: 871–890. https://doi.org/10.1068/a32117

Li, W. B.; Yang, C. Z.; Shi, H.; Hao, L. B. 2010. A study on the housing price model based on sub-markets, *Urban Problems* (10): 61–66.

Ma, M. L.; Lv, B.; Feng, C. C. 2008. A GIS-based study on spatial pattern of Beijing's housing price, *Natural Resource Economics of China* 21(12): 26–28.

McCord, M.; Davis, P. T.; Haran, M.; McGreal, S.; McIlhatton, D. 2012. Spatial variation as a determinant of house price, *Journal of Financial Management of Property and Construction* 17(1): 49–72. https://doi.org/10.1108/13664381211211046

McMillen, D. P.; Redfearn, C. L. 2010. Estimation, interpretation, and hypothesis testing for nonparametric hedonic house price functions, *Journal of Regional Science* 50: 712–733. https://doi.org/10.1111/j.1467–9787.2010.00664.x

Michaels, R.; Smith, V. 1990. Market segmentation and valuing amenities with hedonic models: the case of hazardous waste sites, *Journal of Urban Economics* 28: 223–242. https://doi.org/10.1016/0094–1190(90)90052-O

Osland, L. 2010. An application of spatial econometrics in relation to hedonic housing price modeling, *Journal of Real Estate Research* 32(3): 289–320.

Páez, A.; Fei, L.; Farber, S. 2008. Moving window approaches for hedonic price estimation: an empirical comparison of modelling techniques, *Urban Studies* 45(8): 1565–1581. https://doi.org/10.1177/0042098008091491

Qian, Z. 2015. City profile: Hangzhou, *Cities* 48: 42–54. https://doi.org/10.1016/j.cities.2015.06.004

Quigley, J. 1985. Consumer choice of dwelling, neighborhood and public services, *Regional Science and Urban Economics* 15: 41–63. https://doi.org/10.1016/0166–0462(85)90031–6

Saefuddin, A.; Yekti, W. 2012. Land price model considering spatial factors, *Asian Journal of Mathematics and Statistics* 5(4): 132–141. https://doi.org/10.3923/ajms.2012.132.141

Schnare, A.; Struyk, R. 1976. Segmentation in urban housing markets, *Journal of Urban Economics* 4: 146–166. https://doi.org/10.1016/0094–1190(76)90050–4

Shi, Y. S.; Guo, H. N. 2009. Analysis on temporal and spatial effects of Shanghai South railway station on housing prices, *Acta Geographica Sinica* 64(2): 167–176.

Söderberg, B.; Janssen, C. 2001. Estimating distance gradients for apartment properties, *Urban Studies* 38(1): 61–79. https://doi.org/10.1080/00420980123880

Theriault, M.; Des Rosiers, F.; Villeneuve, P.; Kestens, Y. 2003. Modelling interactions of location with specific value of housing attributes, *Property Management* 21(1): 25–62. https://doi.org/10.1108/02637470310464472

Wang, D.; Huang, W. S. 2007. Effect of urban environment on residential property values by hedonic method: a case study of Shanghai, *City Planning Review* 31(9): 34–41.

Wang, X.; Zhu, D. L. 2004. The application of geostatistics in the study on spatial distribution discipline of metropolitan house prices: a case study of Beijing, *China Soft Science* (8): 152–155.

Wei, C. H.; Qi, F. 2012. On the estimation and testing of mixed geographically weighted regression models, *Economic Modelling* 29: 2615–2620. https://doi.org/10.1016/j.econmod.2012.08.015

Wen, H. Z.; Bu, X.; Qin, Z. 2014b. Spatial effect of lake landscape on housing price: a case study of the West Lake in Hangzhou, China, *Habitat International* 44: 31–40. https://doi.org/10.1016/j.habitatint.2014.05.001

Wen, H. Z.; Tao, Y. 2015. Polycentric urban structure and housing price in the transitional China: evidence from Hangzhou, *Habitat International* 46: 138–146. https://doi.org/10.1016/j.habitatint.2014.11.006

Wen, H. Z.; Zhang, L.; Peng, L. F. 2010. Spatial variation of housing prices in Hangzhou city: two-dimensional analysis based on hedonic prices, *China Land Science* 24(2): 51–56.

Wen, H. Z.; Zhang, Y.; Zhang, L. 2014a. Do educational facilities affect housing price? An empirical study in Hangzhou, China, *Habitat International* 42: 155–163. https://doi.org/10.1016/j.habitatint.2013.12.004

Wheeler, D. C. 2014. Geographically weighted regression, in M. M. Fischer; P. Nijkamp (Eds.). *Handbook of Regional Science*. Springer-Verlag Berlin Heidelberg, 1435–1459. https://doi.org/10.1007/978–3-642–23430–9

Wheeler, D. C.; Páez, A.; Spinney, J.; Waller, L. A. 2014. A Bayesian approach to hedonic price analysis, *Papers in Regional Science* 93(3): 663–683. https://doi.org/10.1111/pirs.12003

Wheeler, D.; Calder, C. 2007. An assessment of coefficient accuracy in linear regression models with spatially varying coefficients, *Journal of Geographical Systems* 9(2): 145–166. https://doi.org/10.1007/s10109–006–0040-y

Wheeler, D.; Tiefelsdorf, M. 2005. Multicollinearity and correlation among local regression coefficients in geographically weighted regression, *Journal of Geographical Systems* 7(2): 161–187. https://doi.org/10.1007/s10109–005–0155–6

Wu, D. M.; Guo, Z. X.; Chen, H. G. 2008. Impact of lake landscape on urban residential property values in Nanjing, *Resources Science* 30(10): 1503–1509.

Xu, X. H. 1997. Characteristics analysis on spatial distribution of Shanghai's housing prices, *Economic Geography* 17(1): 80–87.

Zhang, Z. L. 2012. *Study on the temporal and spatial effects of the city center on housing prices: a case study of Hangzhou*: Master thesis. Zhejiang University.

Zhou, C. S.; Luo, Y. 2004. Spatial distribution and influence of the real estate prices in Guangzhou in the last ten years, *City Planning Review* 28(3): 52–56.

Zhou, M.; Zhen, F. 2008. Study based on the spatial distribution of residential price: taking Nanjing's houses for sale as an example in 2007, *Modern Urban Research* 23(7): 47–53.