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Driving Forces Analysis for Residential Housing Price in Beijing

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Abstract

Previous research showed that various factors could influence the housing market. In this paper, hedonic pricing method was employed to analyze the effects of structural variables, including land transaction price, the distance to downtown area, central business district, railway station and hospital, floor area ratio (FAR), number of bus lines nearby and dichotomous variables, including nearness to rail transit, recreational facilities and parks which reflects the accessibility and living conditions, on housing transaction price. Hedonic pricing models including linear and semi-logarithm regression model were constructed. Results showed that the semi-logarithm model had relatively stronger explanatory power than linear model. The main determinants of housing transaction price in Beijing city were land transaction price, FAR and the distance between housing to downtown area. Among which, transaction price of located land had notably raised housing transaction price, contributing 98.8% to the selling price. FAR and distance from housing to the downtown area were the main negative driving forces for housing transaction price. Compared with structural variables, though correlation analysis indicated that nearness to rail transit and existence of recreational facilities had significant positive correlation with housing transaction price, it was not demonstrated in the regression results. In this study, wavelet-based denoising method was tentatively employed in pretreating data for semi-logarithmic models, and result suggested that the explanatory power of semi-logarithm regression was enhanced.

Key words: Housing price; Wavelet transformation and denoising; Hedonic pricing method; Beijing

1. Introduction

Over the past three decades, rapid economic development has resulted in an increasing demand for residential housing among urban residents. During that time, China has witnessed a drastic increase in transaction prices for residential housing, especially in megacities such as Beijing, Shanghai and Guangzhou [1]. But corresponding modifications in policies and practices have not accompanied this drastic increase in housing prices. This contradiction has become more and more obvious during the rapid urbanization process.

Housing is not a homogeneous commodity [2]. Besides a dwelling, a housing buyer also purchases a set of site characteristics [3]. Various studies on residential housing prices had been conducted to inform housing market

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policy and decision-making. Studies on the relationship between the transaction price of land and housing hav shown that housing transaction prices are positively correlated with land transaction prices, but opinions differ c the precise relationship between the two [4-5]. Abundant research on the driving forces of housing prices sugges that a variety of factors influence housing transaction prices [6]. From a macroscopic perspective, consum purchasing power, product cost, number of enterprises, per capita resources, investment conditions and tax polici may affect housing transaction prices [7], while microcosmic factors affecting the housing market include windo orientation, apartment floor area, and attributes that influence the housing environment, such as view, exposure traffic noise, proximity to woods, proximity to bodies of water, et cetera [8-13]. The hedonic pricing method h been widely applied in these studies to estimate the value of nature connected to settlements [14-16].

In 1964, the American land economist Alonso proposed that rent decreases with increasing distance fro downtown areas, based on the monocentric assumption [17]. However, it is not uncommon for rapidly urbanizir cities to have multiple centers, and research on polycentric cities has become more prevalent [18-19]. Howeve compared with research in Western countries, there have been far fewer empirical studies in China.

This study aims to identify the determinants of housing prices in Beijing, and to clarify how and to what exte these factors affect residential housing prices. A wavelet-based denoising method was employed in this study as method for pre-treating tested data. The findings of this study have some implications regarding the main drivir forces of housing markets in the context of Chinese society..

2. Data and methodology

2.1. Study area

As the capital of China, the city of Beijing covers a land area of 16, 410.5 km^2 and consists of 16 districts. Tl investment in housing projects is presented in Table 1. The development of real estate is consistent with the trend (urbanization and development. The rapid increase of local gross domestic product has stimulated housing deman There has been an increasing trend of investment in the housing market since 2004.

Table 1. Indicators of housing market in Beijing in 2004-2008

Attribute	2008	2007	2006	2005	2004
Gross domestic product per capita (RMB)	63029	58204	50407	45444	41099
Investment in real estate (billion RMB)	1908.7	1995.8	1719.9	1525.0	1473.3
Floor area with commenced construction (ha)	10014.3	10438.6	10483.5	10748.5	9931.3
Finished floor area (ha)	2558.0	2891.7	3193.9	3770.9	3067.0
Sold floor area (ha)	1335.4	2176.6	2607.6	2803.2	2472.0
Population (million)	16.95	16.33	15.81	15.38	14.93

Source: Beijing statistical yearbook (2005-2009).

In this study, Xicheng District, Dongcheng District, Chaoyang District, Chongwen District, Xuanwu Distric Fengtai District, Haidian District and Shijingshan District, which constitute the downtown area of Beijing, we used as the study area.

2.2. Data collection

In this study, a transaction dataset of 73 transaction points were obtained from the Beijing Administrative Bure for Real Estate (Fig. 1). Variables of the dataset are described in Table 2.

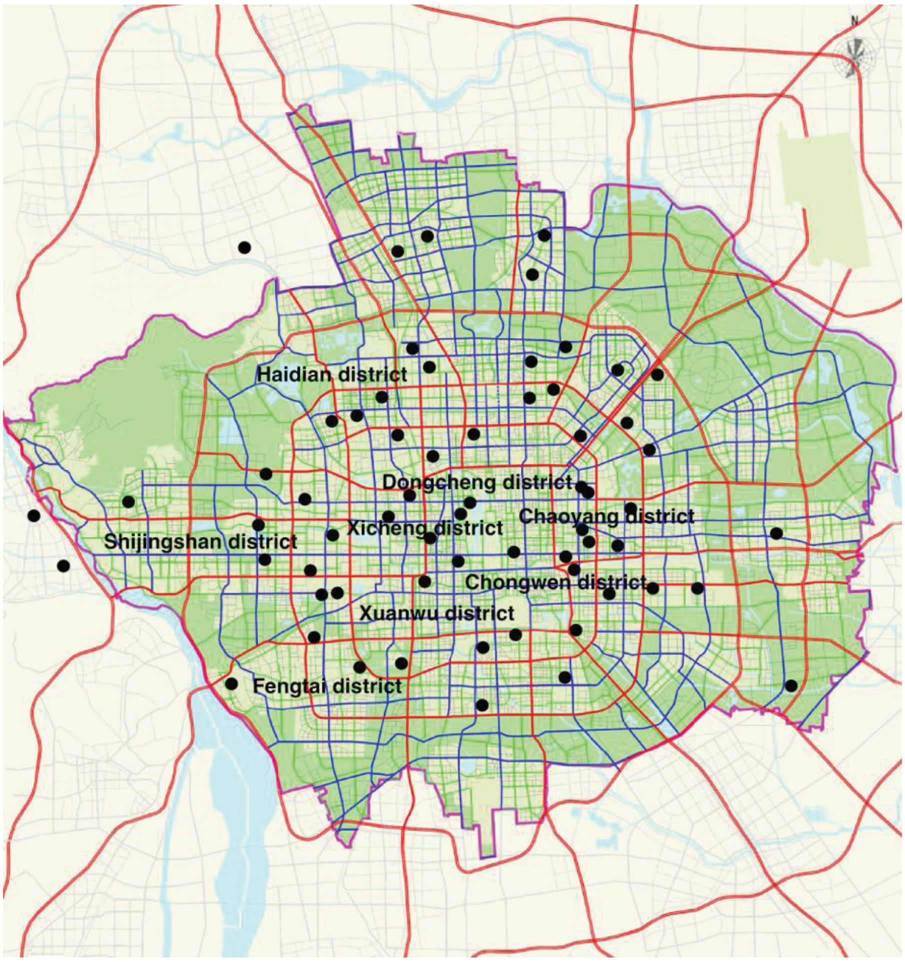

Fig. 1. Spatial distribution of the transaction points

Table 2. Variable descriptions and expected effects on housing transaction price

Variable name	Description	Unit	Expected sign[a]
PRICE	Housing price in transaction samples	RMB	
BLINE	Number of bus lines near the trading housing	Count	?
DCBD	Distance between the trading housing and the central business district	km	-
DCENTER	Distance between the trading housing and the downtown area	km	-
DHOSPITAL	Distance between the trading housing and the nearest hospital	km	?
DPARK	Distance between the trading housing and the nearest park	km	?
DROAD	Distance between the trading housing and nearest road	km	-
DRSTATION	Distance between the trading housing and the railway station	km	?
DSCHOOL	Distance between the trading housing and the nearest school	km	-
FAR	A measure of the ratio of the total area of buildings on a certain location to the size of the land of the location	–	-
PLAND	Land price in transaction samples	RMB	+
RTRANSIT	Existence of rail transits near the trading housing	0, 1	-
FACILITY	Existence of facilities near the trading housing	0, 1	+
PARK	Existence of parks near the trading housing	0, 1	+

[a] + and – represent increasing and decreasing effects (respectively) on the residential housing pricing; ? indicates an undetermined sign.

2.3. Wavelet transform and denoising

As the economic system becomes more complex, the information contained in economic time series datasets becomes more abundant, and is influenced by many factors. Since such influence can be nonlinear with uncertainty, traditional economic quantitative methods are greatly limited in model construction. As a kind of time series data, economic data are similar to engineering signals in that both contain information and can be observed. In signal processing, useful information is separated from redundant information using certain techniques, allowing relationships between studied objects to be more easily established. This principle also applies to the treatment of time series data such as economic data.

In this study, the housing transaction dataset is regarded as noisy signals, and a wavelet-based denoising method was tentatively employed to pre-treat the original dataset. The denoising process is presented in Fig. 2.

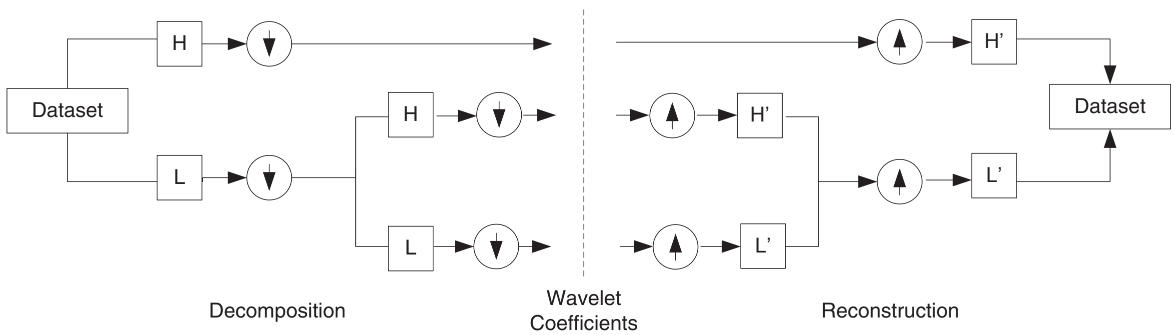

Fig. 2. Main steps of wavelet-based denoising

Traditionally, Fourier transform-based spectral analysis has been the dominant analytical tool for frequency domain analysis in signal processing. However, Fourier transform cannot provide information on spectrum changes with respect to time. As an alternative mathematical tool, wavelet transform can extract relevant time-amplitude information from a signal. In the meantime, the signal-to-noise ratio of the original signal can be improved based on prior knowledge of the signal characteristics.

First, wavelet transform was applied to the observed dataset to produce the noisy wavelet coefficients to the desired level. The general formula of continuous wavelet transform is as follows:

$$W_f(a,b) = f(b) * \psi_a(b) = \frac{1}{\sqrt{a}} \int_{t=-\infty}^{+\infty} f(t) \psi\left(\frac{b-t}{a}\right) dt \quad (1)$$

where a, b are dilating and translating coefficients, respectively, and $\psi(t)$ is the selected analysis function. The wavelet transform decomposes the signal into different scales with different levels of resolution by dilating a single prototype function. But the result of the CWT is often redundant. Thus, the dataset can be completely reconstructed by a simple version of $W_f(a,b)$. Typically, let:

$$a = 2^{-m} \text{ and } b = n2^{-m}$$

then equation (1) is rewritten:

$$DWT_\psi f(m,n) = \int_{-\infty}^{\infty} f(t) \psi_{m,n}(t) dt \quad (2)$$

where $\psi_{m,n}(t) = 2^{-m} \psi(2^m t - n)$ is the dilated and translated version of the mother wavelet $\psi(t)$.

Then, appropriate threshold limits are selected at each level and a thresholding method (hard or soft thresholding) is applied to effectively remove noise. In this study, the Stein unbiased risk estimate method is adopted for its high denoising efficiency:

$$T = \sigma \sqrt{\omega_b} \quad (3)$$

where σ is the noise intensity of a given decomposing level, and ω_b is the wavelet coefficient corresponding to the minimum risk value of the given level.

Then, the wavelet transformation of the thresholded wavelet coefficients is inversed and the denoised dataset is obtained.

2.4. Hedonic pricing method

Housing is a commodity with various characteristics, such as location, structure, floor area, window orientation et cetera. These characteristics determine the housing transaction price. When some of the characteristics change, the transaction price changes according to a certain ratio. Based on the hedonic hypothesis, the implicit prices of spillover benefits from the neighborhood or environmental characteristics can be reflected. The traditional hedonic pricing model is as follows:

$$P = f(x_1, x_2, \cdots, x_n) \quad (4)$$

where P is the housing transaction price and $x_1, x_2, \cdots, x_n$ are variables reflecting the property's characteristics.

Multiple regression techniques have been employed in hedonic pricing models to relate property price details to diverse characteristics of differing properties, and to sort the differing properties and the contributions made by each characteristic. But there is no concensus on the functional form of the hedonic pricing method due to insufficient guidance from economic theory on the intricate relationship between housing prices and various housing characteristics. So, different functions, including linear, semi-logarithmic, double logarithmic and Box-Cox, have been adopted in previous studies. Previous research suggests that Box-Cox transformation is more effective than other transformations, and could yield a better fit of data. The main shortcoming of Box-Cox is that it requires a complicated transformation process, which could result in more random errors. Compared with Box-Cox transformation, the results of other transformations are much easier to apply and have a relatively strong explanatory power in cases of missing explanatory variables [19]. Following previous studies [20-22], linear and semi-logarithmic hedonic pricing models were adopted with multiple regression analysis in our study.

2.5. Model construction

In this study, two functional forms were constructed to explore the relationship between housing transaction prices and housing attributes. When the relationship is assumed to be linear, the hedonic pricing model is as follows:

$$PRICE = \alpha + a_1\ x_1 + a_2\ x_2 + \cdots + a_n\ x_n \qquad (5)$$

where α is the constant and a_1 - a_n are marginal willingness-to-pay for each attribute.
When the estimated equation is assumed to be semi-logarithmic, the functional form is expressed as follows:

$$\ln\ PRICE = \beta + b_1\ \ln x_1 + b_2\ \ln x_2 + \cdots + b_m\ \ln x_m + b_{m+1} x_{m+1} + \cdots + b_n\ x_{\mathrm{n}} \qquad (6)$$

where β is the constant, and b_1 - b_n are price elasticity with respect to each estimator. Dichotomous variables x_{m+1} - x_n were not log-transformed.
To evaluate the effect of the wavelet-based denoising method on the explanatory power of the regression model, another model was established in the semi-logarithm form:

$$\ln\ PRICE' = \beta' + b_1'\ \ln x_1' + b_2'\ \ln x_2' + \cdots + b_3'\ \ln x_m' + b_{m+1}' x_{m+1}' + \cdots + b_n'\ x_n' \qquad (7)$$

The framework of this study as a whole is presented in Fig. 3.

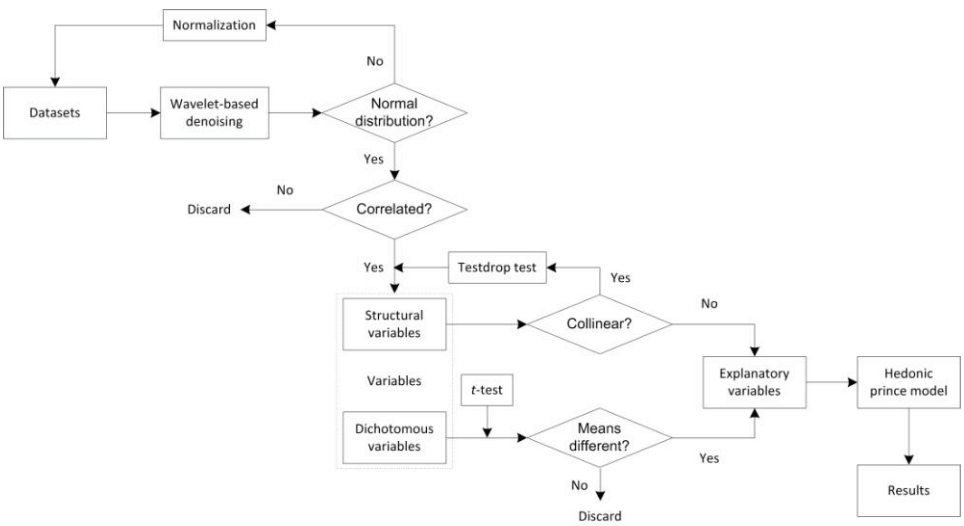

Fig. 3. Study framework

3. Results

3.1. Correlation analysis and t-test

Results of correlation analysis are presented in Table 3, which shows that the main factors that correlate with housing transaction price are the number of bus lines nearby, the distances from the housing to the CBD, downtown area and rail station, floor area ratio of the housing and the transaction price of the land. Of these, land transaction price had a significant positive correlation with housing transaction price ($r = 0.939$). The distances to hospitals and parks appear to have little effect on housing transaction prices.

Table 3. Correlation analysis results of variables

Variable	PRICE	BLINE	DCBD	DCENTER	DHOSPITAL	DPARK	DROAD	DSTATION	DSCHOOL	FAR	PLAND
PRICE	1	0.736**	0.298**	-0.828**	-0.050	-0.114	-0.101	-0.828**	-0.114	0.384**	0.939**
BLINE		1	0.159	-0.857**	-0.306**	-0.064	0.159	-0.869**	-0.282*	0.543**	0.784**
DCBD			1	-0.205	0.321**	0.329**	0.364**	-0.300*	0.289*	-0.299	0.122
DCENTER				1	0.260*	0.089	0.196	0.971*	0.294*	-0.585**	-0.861**
DHOSPITAL					1	0.481**	0.168	0.238*	0.585**	-0.432**	-0.202
DPARK						1	0.341**	0.110	0.249*	-0.229	-0.822**
DROAD							1	-0.172	0.018	0.304**	-0.047
DSTATION								1	0.228	-0.485**	-0.822**
DSCHOOL									1	-0.475**	-0.267*
FAR										1	0.676
PLAND											1

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Correlation analysis results also show that the independent variables were closely correlated. For example, the correlation between housing transaction price and the distance from the housing to a rail station was -0.828 (significant at 0.01 level), suggesting probable collinearity between independent variables. To avoid collinearity, the testdrop method is employed. The testdrop method offers a simple method for testing collinearity between independent variables. When the absence of a specified variable has little influence on the regression model, it is alternative or extraneous. The testdrop method can be processed with common statistics software such as Eviews. Test results show that the number of bus lines near housing has little effect on the regression model. Thus, the structural variables selected are distance from housing to downtown area (DCENTER), floor area ratio and the transaction price of the land (PLAND).

Variables including FACILITY, PARK and RTRANSIT are dichotomous variables, which are categorized into two groups to denote whether the housing has facilities (FACILITY), parks (PARK) or nearby rail transit (RTRANSIT). In this paper, a *t*-test was employed to identify the effects of these attributes on housing transaction prices. Results show that recreational facilities and rail transit have significant effects on housing transaction prices, whereas the amenity value of nearby parks is not obvious (Table 4).

Table 4. Results of t-test for dichotomous variables

Dichotomous Variable	*t*-Ratio	*p*-Value	Std. Error	95% Confidence interval
FACILITY	-2.638	0.010	0.189	(-0.877, -0.122)
PARK	-0.498	0.620	0.196	(-0.489, 0.293)
RTRANSIT	-3.759	0.000	0.234	(-1.347, -0.413)

Factor analysis is a statistical method used to describe variability among observed variables in terms of a potentially lower number of unobserved variables called factors. In other words, it is possible, for example, that two or three observed variables together represent another, unobserved variable, and factor analysis searches for these possible combinations. The information gained about interdependencies between observed variables can be used later to reduce the set of variables in a dataset. The results of factor analysis of selected independent variables are presented in Table 5.

Table 5. Factor analysis of selected independent variables (rotated component matrix)

Variable	Component		
	1	2	3
DCENTER	-0.810	-0.321	-0.114
FAR	0.816	-0.004	0.135
PLAND	0.865	0.216	0.289
FACILITY	0.184	0.966	0.033
RTRANSIT	0.230	0.034	0.971

Factor analysis results indicated that the first component is closely related to land transaction prices, suggesting that the influence of land transaction price on the housing transaction price is important. The second and third components are closely related with the dichotomous variables FACILITY and RTRANSIT, respectively, which reflects the importance of accessibility and the amenity value of recreational facilities. The cumulative variance of these three components contributes 85.97% of the total, which suggests that the selected factors reflect most of the information.

3.2. Wavelet transform and denoising

Results of wavelet-based denoising of the independent variables are shown in Fig. 4. The denoised dataset fit well with the observed dataset, and contain most of the original information.

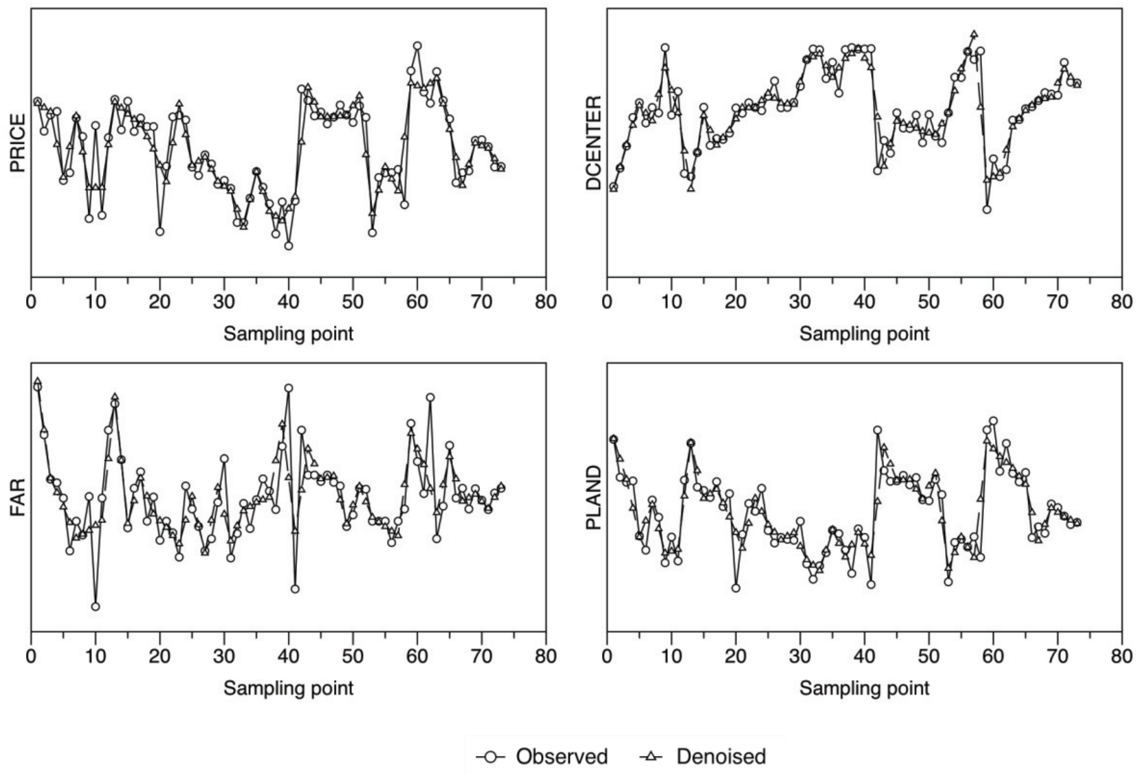

Fig. 4. Comparison of denoised data sets and observed data sets

3.3. Hedonic pricing regression

Results of the estimators of the linear model and semi-logarithmic model are shown in Tables 6 and 7, respectively. Compared with the linear regression model, the explanatory power of the semi-logarithmic model is higher (R^2 = 0.993). Estimators in Tables 7 and 8 indicate that the wavelet-based denoising method is applicable and effective in data pre-treating for the hedonic pricing regression model. The explanatory power of the semi-logarithmic model employing the wavelet-based denoising method is higher than the linear regression model and single semi-logarithmic model (R^2 = 0.998).

The effects of the independent variables revealed by these models are similar. All models attributed the bulk of the selling price mainly to floor area ratio and land transaction price. The sign (positive and negative) of the three structural variables, including the distance between the housing and the downtown area, floor area ratio and land transaction price, are statistically significant and consistent with expectations (Table 7). In contrast, the remaining dichotomous variables, including the proximity of rail transit and facilities, are statistically non-significant, and their signs contrasted with expectations (Tables 6, 7 and 8). The variance inflation factor (VIF) indicates that there is no collinearity among independent variables in all models.

The land transaction price has a considerable effect on the housing transaction price. Higher land prices result in higher housing transaction prices. All models assigned importance to this attribute (*t*-ration at 13.904, 58.031 and 91.921, respectively). The result is consistent with common sense. The higher the cost paid by the real estate developer, the higher the housing transaction price will be, regardless of other conditions, such as the environment, amenities or accessibility.

Floor area ratio is the ratio of the total construction area to the land area in a specified residential area. It reflects residential density to some extent. Higher floor area ratios reflect in higher construction density, which leads to lower living comfort for residents [23]. The regression results verify this relationship. Lower floor area ratios indicate more living space for each person, whereas higher ratios lead to less desirable dwellings dominated by other buildings, such as offices for commercial use.

In this study, the distance between housing and the downtown area was not found to be as important a factor in housing transaction price. The implicit price estimates offered by semi-log coefficients and semi-log based on wavelet transform and denoising coefficients both assigned 3.0% of the transaction housing price to the distance between housing and the downtown area. Traditionally, in a monocentric city, people prefer to live near the downtown area. However, the development of modern cities has led to an increase in polycentrism, especially in megacities. Together with rapid progress in urban infrastructure construction, distance to the downtown area appears to be less than before. This change may help to explain why this attribute been suppressed in making buying decisions.

Contrary to our expectations, the positive effects of nearby rail transit were not demonstrated in the regression models (t-ration at -0.265, 0.196 and -0.874, respectively). Results of correlation analysis show that the existence of rail transit nearby is positively correlated with housing transaction prices (r = 0.325, significant at 0.01 level). Similar results were found concerning the effect of facilities on housing transaction prices (t-ration at 1.145, -0.643 and -0.490, respectively; r = 0.281, significant at 0.01 level). This somewhat unexpected finding might result from an insufficient data sample.

Table 6. Results of estimation of linear regression model (dependent variable, PRICE)

Explanatory variable	Coefficient	Std. Error	*t*-Ratio	*p*-Value	VIF
DCENTER	-0.014	0.005	-2.670	0.009	1.443
FAR	-641.214	106.450	-6.032	0.000	2.405
PLAND	0.261	0.019	13.904	0.000	2.319
FACILITY	206.867	185.375	1.145	0.268	1.173
RTRANSIT	-69.308	249.336	-0.265	0.782	1.271
Constant	2379.272	265.537	8.962	0.000	-

R^2 = 0.851, adjusted R^2 = 0.840, F-ratio = 76.425, n = 73.

Table 7. Results of estimation of semi-logarithmic regression model (dependent variable, ln PRICE)

Explanatory variable	Coefficient	Std. Error	*t*-Ratio	*p*-Value	VIF
DCENTER	-0.030	0.017	1.655	0.083	3.032
FAR	-1.023	0.026	-38.288	0.000	2.525
PLAND	0.979	0.017	58.031	0.000	4.154
FACILITY	-0.016	0.018	-0.643	0.381	1.186
RTRANSIT	0.002	0.025	0.196	0.937	1.306
Constant	0.471	0.273	1.666	0.090	-

R^2 = 0.993, adjusted R^2 =0.992, F-ratio = 1914.280, n = 73.

Table 8. Results of estimation of semi-logarithmic regression model based on wavelet analysis (dependent variable, ln PRICE)

Explanatory variable	Coefficient	Std. Error	*t*-Ratio	*p*-Value	VIF
DCENTER	-0.030	0.011	-3.070	0.003	3.918
FAR	-1.041	0.018	-56.572	0.000	1.871
PLAND	0.988	0.011	91.921	0.000	5.008
FACILITY	-0.005	0.009	-0.490	0.626	1.133
RTRANSIT	-0.011	0.012	-0.874	0.385	1.173
Constant	0.433	0.178	2.432	0.018	-

R^2 = 0.998, adjusted R^2 = 997, F-ratio = 5659.656, n = 73.

4. Discussion

4.1. Wavelet-based denoising method

Wavelet transformation methods have been widely used in signal processing. As an alternative tool, the main advantage of wavelet analysis is that it can extract the relevant time-amplitude information from a signal together with frequency information, and can improve the signal-to-noise ratio based on prior knowledge of the signal characteristics. In this study, observed data sets were transformed with mother wavelet Bior 2.2 at decomposition level 1. The threshold was set with the Stein unbiased risk estimate method. Regression results show that semi-logarithmic regression based on wavelet transformation and denoising has more explanatory power than other methods. But problems such as unexpected results regarding the role of facilities and rail transit cannot be solved with denoising. The inefficiency of the regression model employing denoising could be due to factors such as mother wavelet selection, threshold setting or the decomposition level of the original dataset, which determine the denoising quality. Mother wavelets should be carefully selected to better approximate and capture the transient spikes of the original signal. The threshold-setting method should be undertaken cautiously as well. In further research, the determination of key parameters in wavelet-based denoising and application should be further studied.

4.2. Hedonic pricing method

In Western housing markets, the hedonic pricing method has proven an effective technique for real estate valuation. Successful application of the hedonic pricing method is mainly determined by the degree of development and openness in regional real estate markets, which provide sufficient transaction information. This is important in eliciting reliable estimations. The different models employed in this paper have relatively high explanatory power. Most of the findings in this paper concur with previous studies, both domestic and foreign. All models showed that land transaction prices considerably enhance housing transaction prices. Proximity to rail transit and existence of facilities correlate with housing transaction prices, but the value of accessibility and the amenity value of parks and facilities were not demonstrated in this study. This might result from an insufficient data sample. Limited data are likely to result in biased results. Thus, further research should be carried out based on more comprehensive data.

5. Conclusion

The hedonic pricing regression model was successfully applied in this study. Results show that the main driving force for housing transaction price in Beijing is floor area ratio, followed by land transaction price. Floor area ratio is positive correlated with housing transaction price, and land transaction price is the main negative factor for housing transaction price. This is consistent with the prevailing understanding of the real estate market in China.

In this study, the wavelet-based denoising method is tentatively employed in data pretreating. The explanatory power of the semi-logarithmic regression model based on wavelet denoising was stronger than the linear regression model and raw semi-logarithmic model, suggesting that wavelet denoising is effective in pre-treating tested datasets.

Contrary to expectations, the effects of some housing attributes were not demonstrated by all models, such as the effect of nearby rail transit in the linear regression model, and the proximity of facilities in semi-logarithmic models, whose sign contrasted with common sense. This may due to insufficient transaction data, which lead to biased statistical results.

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