Purchase Motivation, Landscape Preference, and Housing Prices: Quantile Hedonic Analysis in Guangzhou, China

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Abstract: Urban landscapes are important factors that affect housing prices, and significant differences between landscape preferences of various homebuyers may be observed because of the different reasons for purchasing a house (consumption or investment). However, the hedonic price model widely applied in most existing studies only captures the average effects of landscapes as a whole sample, and may ignore the heterogeneity of landscape preferences. To fill this gap, this study constructed hedonic price models and quantile regression models with the housing data in Guangzhou, China from 2013 to 2016 and analyzed the landscape preferences of buyers with different purchase motivations. Empirical results showed that the landscape preferences of buyers were different in housing submarkets. The implicit value of landscapes was greater in consumption demand than in investment demand, whereas investment buyers were more vulnerable to the disamenity effect of unattractive landscapes. In addition, the quantile effect of landscapes was identified, in which the buyers of high-priced housing will pay more for high-quality landscapes. This study revealed the diversified housing demands and landscape preferences of homebuyers, which is important for urban planning and project development. DOI: 10.1061/(ASCE)UP.1943-5444.0000734.

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Introduction

In July 1998, the Chinese government formally abolished the welfare housing system with a strong focus on a planned economy, and implemented a policy of "housing monetization," which gradually led the real estate market toward marketization, where urban residents could only solve their housing problems through the housing market. Over the past 20 years, the Chinese real estate industry, driven by a strong housing demand, has developed rapidly. The rapid increase in housing prices has aroused the attention of people from all walks of life, and discussions about "overheating" or "bubbles" in real estate have been evident. Although the Chinese urban housing market is dominated by consumption demand, investment demand also exists (Zhang and Lee 2014; Zheng and Liu 2005). Paying attention to the housing demands and preferences of buyers is extremely important – urgent even – for a comprehensive understanding of the housing market in Chinese cities. Therefore, this study attempted to divide the urban housing market according to purchase motives, explored in depth the determinants of housing prices in different submarkets, and revealed the heterogeneous preferences of buyers in relation to consumption and investment demands.

We focused on the landscape preferences of homebuyers. Landscape is an important factor that has a significant effect on housing prices. The majority of studies have been carried out on mature housing markets in Western countries. Several scholars have found that urban landscapes, such as parks (Votsis 2017; Poudyal et al. 2009), wetlands (Tapsuwan et al. 2009; Mahan et al. 2000), lakes (Loomis and Feldman 2003), and oceans (Hamilton and Morgan 2010; Latinopoulos 2018), can increase the surrounding housing prices significantly. In recent years, the relationship between landscapes and housing prices has attracted the attention of Chinese scholars. Hui et al. (2012) found that proximity to a park or a Seaview would increase housing prices by 5.94% and 6.03%, respectively, whereas a nearby street can have a negative impact on housing prices in Hong Kong. Kong et al. (2007) used a hedonic price model with six spatial variables that were measured according to the richness, density, and aggregation of landscapes to capture the amenity effects of green space and land-use spatial patterns on the surrounding houses in Jinan. Wen et al. (2015) revealed that people are willing to pay extra for environmental amenities in Hangzhou. Specifically, a 1% decrease in the distance to Westlake and nearby parks resulted in a 0.229% and 0.052% premium, respectively.

These studies used the hedonic price model to evaluate the average amenity effect of landscape features for the whole market, with the implicit assumption that the effects of landscapes will be the same for houses at different price levels in housing submarkets. However, this assumption may not be consistent with the actual situation. For one thing, buyers with different purchase motivations have diversified psychological preferences and decision-making behaviors, meaning housing preferences may vary significantly. For another, buyers of housing at different prices are often from different economic classes. High-income buyers, for example, are in a better position to choose a house with good landscapes and are willing to pay higher prices for such houses, thereby making their living conditions more comfortable and convenient (Mak et al. 2010; Wen et al. 2018). Under the impetus of different purchase motives, housing preferences, and income, buyers are therefore attracted by different types of housing, and this behavioral heterogeneity cannot be described simply by an average effect (Schnare and Struyk 1976; Soguel et al. 2008). To fill this gap and extend the former research, this study constructed hedonic price models and quantile regression models with housing data in Guangzhou, China from 2013 to 2016 to explore the relation among purchase motivation, landscape preference, and housing price. The questions posed were as follows. (1) Considering the three dimensions of accessibility, visibility, and availability, do landscape features have amenity or disamenity effects on housing prices? (2) Dividing housing submarkets according to purchase motive, are there substantial differences in landscape preferences between consumption demand and investment demand? (3) Do the amenity effects of landscapes vary significantly across different price levels? If a difference does exist, what are the landscape preference patterns for low-, medium-, and high-priced housing?

This study proposes three main contributions that could have guiding significance for urban planners to improve the living environment: (1) it focuses on several types of urban landscapes, and comprehensively explores the amenity and disamenity effects of landscapes on housing submarkets from the dimensions of accessibility, visibility, and availability; (2) consistent with the Chinese housing market, this study classifies buyers into consumption homebuyers (further subdivided into first-time and improvement homebuyers) and investment homebuyers; in doing so, it accesses the heterogeneous landscape effects on different housing submarkets; and (3) as in improvement on the traditional model, quantile regression is used to measure the effects of landscapes across the conditional quantile distribution, thereby revealing in depth the heterogeneity of homebuyer landscape preferences. This study illustrates the importance of dividing housing submarkets when estimating landscape effects. In the context of the coexistence of consumption and investment demand in the Chinese housing market, these results may encourage government planners to re-examine urban landscape planning and land-use policies from the perspective of housing demand, and could also be crucial for real estate developers and buyers.

Literature Review

With the improvement of living standards and the rise in consumption levels, urban residents are paying increasing attention to the surrounding landscapes when making purchase decisions. A large amount of literature has demonstrated that urban landscapes have amenity effects on housing prices (Bolitzer and Netusil 2000; Cho et al. 2011; Sander and Polasky 2009; Gibbons et al. 2014; Wen et al. 2014; Schaeffer and Dissart 2018). Three types of landscape infrastructure, namely, green infrastructure (e.g., green spaces, parks, forests, and mountains), blue infrastructure (e.g., lakes, rivers, oceans, and rivers), and gray infrastructure (e.g., streets, viaducts, and buildings), have attracted the attention of scholars the most (Svendsen et al. 2012; Alves et al. 2019; Gunawardena et al. 2017). To assess the effects of the aforementioned landscape elements on housing prices, physical and spatial attributes of the landscape have received extensive attention from scholars (Melichar and Kaprová 2013; Mittal and Byahut 2016; Schläpfer et al. 2015).

Physical attributes are the basic properties of urban landscapes, and the amenity effects vary with the type, scale, and quality of urban landscapes. For example, Wen et al. (2015) found that different types of urban landscapes had significant amenity effects on the housing prices in Hangzhou: the premium effects that the Qiantang River, parks, squares, mountains, and West Lake had on surrounding housing prices varied significantly. Lutzenhiser and Netusil (2001) classified parks into natural parks, urban parks, and specialty parks, to examine the relationship between landscape proximity and housing price. The findings showed that all categories of park have positive significant impacts on the cost of houses that are located within 200 ft of them, with natural parks having the largest impact. Larson and Perrings (2013) explored the effect of different park sizes on housing prices in Phoenix, and found that small-sized parks have a negative effect on housing prices, whereas large-sized parks can generate a premium effect. Poudyal et al. (2009) revealed that the effects of parks are related to their expanse. For every 1% increase in park area within a 1-mi radius of a residential house, the housing price increases by 0.03%, that is, every additional 100 ft^2 of park area will bring a premium of USD 80. Bin and Czajkowski (2013) and Chen (2017) focused on water pollution and restoration from the perspective of landscape quality and found that an improvement in water quality was beneficial to residents and raised housing prices. Stigarll and Elam (2009) studied landscape quality in Melonie Park, Lubbock, and concluded that an improvement in landscape quality, from average quality to good and excellent, will increase housing prices by a premium of 5.7% and 10.8%, respectively.

More studies focus on the spatial attributes of landscapes and often use accessibility and visibility indicators to capture the amenity effect of landscapes. The amenity effect varies according to the house location. Euclidean distance (Poudyal et al. 2009), grid distance (Lu et al. 2014), and cost-weighted distance (Kong et al. 2007) are basic methods of measuring landscape accessibility. However, some scholars have attempted to find more accurate calculation methods to measure landscape accessibility, for example, the gravity model that considers distance attenuation and the supply–demand relationship (Hillsdon et al. 2006; Wu et al. 2017), the two-step floating catchment area method that is based on cumulative opportunity measurement (Luo and Wang 2003; Lee and Hong 2013; Cheng et al. 2011), and a measurement model that considers people′s travel preferences and environmental equality (Xu et al. 2017; Xiao et al. 2019; Li et al. 2019). Although existing studies differ in their measurement methods of landscape accessibility, the vast majority of studies indicate that landscape accessibility has a positive effect on housing prices. For example, Du and Huang (2018) estimated the marginal implicit value of the Xixi wetlands in Hangzhou and found that a reduction in distance of 100 m to the Xixi National Wetland Park increased housing prices by 35.7 Yuan. Shi and Zhang (2010) analyzed the amenity effect of the Huangxing Park on housing prices in Shanghai and found that the appreciation in housing prices decreases gradually with increased weighted distance, and that the maximum influence radius of the park was 1,590 m. Landry and Hindsley (2011) studied houses near the beach in Tybee Island, GA, USA and concluded that housing prices decreased by 21%, 39%, and 50% when the house was 100, 200, and 300 m away, respectively, from a high-quality beach.

Landscape visibility means that residents can see landscapes through the doors or windows of a house. A house with beautiful landscape views is likely to provide direct aesthetic amenity value for residents. Chen and Jim (2010) concluded that the implied price of landscape visibility was higher than that of landscape accessibility in Shenzhen. The amenity effect of a garden view was attributed to its aesthetic value, which can bring a premium of 17.2%, and the implicit value of a bay view increased housing prices by 11.2%. Hui and Liang (2016) assessed the spatial spillover effect of landscape visibility in Guangzhou and noted that people are willing to pay a high price to enjoy better environmental conditions and enhanced aesthetic effects; a road view offered a discount of 11% because traffic may result in noise and air pollution. The angle and quality of landscape views are also important for fetching premium prices. In Bellingham, WA, Benson et al. (1998) showed that the value of an ocean view depends largely on the quality of that view. Jim and Chen (2009) assessed two types of natural landscapes in Hong Kong and found that a broad view of a harbor could increase house prices by 2.97%, whereas a narrow view might only bring a premium of 2.18%. However, a broad mountain view reduced housing prices by 6.7%, whereas a narrow view was statistically insignificant. In addition, the study found that a street view had a negative effect on housing prices, resulting in a 3.7% drop. Bin et al. (2008) studied ocean-adjacent houses in North Carolina; they used a geographic information system to create a viewscape to measure a property's degree of ocean view and concluded that people's willingness to pay depends on the degree of the seascape. Specifically, for every 1° increase, the housing price will increase by $995.

The aforementioned studies regarded the cities' housing markets as a whole and constructed the hedonic price model to analyze the overall amenity effect of urban landscapes. However, there is strong evidence that it is important to consider the differences between housing submarkets in large cities. Certain scholars have conducted extended research from the perspective of a housing submarket. For example, Hui et al. (2012) divided the housing market into several submarkets and evaluated the amenity effects of landscape features. Soguel et al. (2008) emphasized the benefits of market segmentation; housing segmentation was tested through a study of six resorts in Switzerland and heterogeneous implicit prices of environmental variables were identified. De Araujo and Cheng (2017) compared the amenity preferences of house and apartment buyers in New York, and found significant differences between the preferences of the two types of buyer, thereby illustrating the importance of distinguishing housing submarkets when evaluating impacts. The Chinese housing market has diverse demands. Du et al. (2017), for example, emphasized the necessity of considering housing demand from the perspectives of consumption and investment. Some residents decide to reside in the property, while others consider the purchase of a house to be an investment behavior. Homebuyers decide on the basis of different purchase motives (i.e., consumption or investment), and their landscape preferences may therefore differ significantly. Evidently, the heterogeneity of such decision-making behavior cannot be summarized simply by an average effect, but few studies have attempted to distinguish between the consumption and investment demands of homebuyers when evaluating the amenity effects of landscapes. Conducting an in-depth study from the perspective of submarkets is therefore of great significance.

Existing studies used the ordinary least squares (OLS) regression method to assess the amenity effects of landscapes, but such results can only reflect the average implicit prices of landscape features. Buyers of different value housing may have disparate preferences for urban landscapes, which may result in a heterogeneous landscape amenity effect at different price levels (Rajapaksa et al. 2017; Malpezzi 2002; Zietz et al. 2008). Quantile regression is superior to OLS in analyzing market heterogeneity because the relationship between housing characteristics and prices is based on the entire conditional distribution, not solely on the conditional mean effect, which therefore offers more comprehensive results (Koenker and Bassett 1978; Buchinsky 1998; Yu et al. 2003). The quantile model is frequently used in social science research, and some attempts to use the model in real estate research have also appeared in recent years because of its unique advantages. For example, Mueller and Loomis (2014) applied a quantile regression model to study how wildfires affect housing prices in Southern California, and found that this effect changed as the conditional distribution of housing prices varied. Mak et al. (2010) indicated that in the Hong Kong housing market, homebuyers of different value housing also have significant differences in their preferences for housing characteristics. Wen et al. (2019) estimated the quantile impacts of educational facilities on housing prices and proved that buyers have different willingness to pay levels for educational facilities. Fernandez and Bucaram (2019) constructed a hedonic study of the housing market based on unconditional quantile regressions in Auckland and found that capitalization models were diverse in different housing submarkets. The quantile regression model provides a more comprehensive description for revealing the heterogeneous amenity effects of landscapes on the housing prices of different conditional distributions. With the more realistic analysis results that can be obtained, the differential behavior of high- and low-end homebuyers can thereby be distinguished effectively. However, only a few scholars have used quantile regression to conduct exploratory research into the amenity effect of landscapes. In the current study, we utilized a quantile regression model to provide relevant empirical results.

In summary, the relationship between landscape effects and housing prices has received increasing attention. These studies have mainly focused on a certain type of urban landscape and revealed its effect on the housing prices of the overall housing market. As a result, there is work to be done. Firstly, a richer variety of landscape types and attributes should be captured to estimate their amenity values. Secondly, very few studies have focused on the complex relationship between purchase motivation, landscape preferences, and housing prices. Evaluating the preferences of buyers with consumption and investment demands in different economic classes will provide us with more accurate results. We attempted to fill these gaps by constructing a traditional hedonic price model and a quantile regression model, and investigated the dissimilarities in the landscape preferences of different types of buyers. This interesting topic is of interest to homebuyers, developers, and urban planners, and warrants further research.

Data and Model

Data and Variable Description

The study area was Guangzhou, Guangdong Province. As a super first-tier city in China, its developed economy and superior geographical location mean the housing market is mature and highly market-oriented. This study covered six administrative regions of Guangzhou, including the districts of Liwan, Yuexiu, Haizhu, Tianhe, Baiyun, and Panyu. By the end of 2016, the urbanization rate of Guangzhou had accelerated to reach 86.06%. To meet the growing housing demand, the supply of high-rise housing has been increasing, and housing with excellent landscapes are even more sought after. In addition to the advantages of geographical location and transport links, homebuyers are increasingly concerned about the quality of the surrounding environment. Urban residents usually have a stronger willingness to pay for houses with green spaces or water features due to their leisure and entertainment functions, and because they improve the living experience of buyers. For example, housing on both sides of the Pearl River is always in short supply. Such landscape features are important to developers and homebuyers.

Table 1. Variable descriptions

Characteristic type	Variables	Variable definition	Expected sign
Dependent variable	Housing price (P)	Transaction price of housing (CNY)	/
Structure characteristic	Area (A)	Building area of housing (m^2)	+
	Floor (F)	Floor level of the building on which housing is located	?
	Top floor (TF)	Dummy variable, 1 if housing is located in top floor; 0 otherwise	−
	Elevator (ELEV)	Dummy variable, 1 if housing is equipped with elevator; 0 otherwise	+
	South (S)	Dummy variable, 1 if housing has windows facing south; 0 otherwise	+
Neighborhood characteristic	Distance to hospital (DH)	Straight-line distance from housing to the nearest hospital (km)	−
	Distance to subway station (DSS)	Straight-line distance from housing to the nearest subway station (km)	−
	Distance to primary school (DPS)	Straight-line distance from housing to the nearest primary school (km)	−
Location characteristic	Tianhe central business district (CBD)	Dummy variable, 1 if housing is located in the Tianhe CBD; 0 otherwise	+
	Distance to business center (DBC)	Straight-line distance from housing to the nearest business center (km)	−
Landscape characteristic	Distance to the Pearl River (DPR)	Straight-line distance from housing to the Pearl River (km)	−
	Distance to urban park (DUP)	Straight-line distance from housing to the nearest urban park (km)	−
	Garden view (GV)	Dummy variable, 1 if housing has view of a residential garden; 0 otherwise	+
	River view (RV)	Dummy variable, 1 if housing has view of river; 0 otherwise	+
	Landmark view (LV)	Dummy variable, 1 if housing has view of landmark; 0 otherwise	+
	Proximity to viaduct (PV)	Dummy variable, 1 if there is a viaduct within 500 m of housing; and 0 otherwise	−
	Proximity to road (PR)	Dummy variable, 1 if there is an urban trunk road within 500 m of housing; 0 otherwise	−
Time-series	Year2014	Dummy variable, 1 if housing was procured in 2014; 0 otherwise	—
	Year2015	Dummy variable, 1 if housing was procured in 2015; 0 otherwise	—
	Year2016	Dummy variable, 1 if housing was procured in 2016; 0 otherwise	—

Transaction data from 2013 to 2016 in Guangzhou were obtained through a real estate agency, and information on housing and homebuyer characteristics were also collected. Following the study of Du et al. (2017), we designed questionnaires for homebuyers that covered family property ownership, to distinguish purchase demand, and purchase motivations. In detail, we classified housing demand into three categories: (a) families who do not own any other property and the purchase motivation is self-occupation (first-time demand); (b) families who own other property and the purchase motivation is to improve the conditions of self-occupation (improvement demand); and (c) families who own other property and the purchase motivation is for renting or property appreciation (investment demand). Moreover, we defined situations (a) and (b) as consumption housing demand, and (c) as investment housing demand. After eliminating missing information and singular value samples, 10,825 valid samples were obtained, including 6,595 (60.9%) first-time housing samples, 3,447 (31.8%) improvement housing samples, and 783 (7.3%) investment housing samples.

The transaction price of housing was selected as the dependent variable and the availability, accessibility, and visibility of landscapes were set as proxies for landscape features. Seven landscape variables, namely, distance to the Pearl River, distance to the urban park, garden view, river view, landmark view, proximity to viaduct, and proximity to road, were selected in this study to investigate amenity effects. To avoid errors caused by incomplete and unreliable data sets, control variables were also selected. The structure variables included housing area, orientation, floor, and elevator. Location variables included the distance from each house to the central business district, and to the nearest shopping center, which reflect the availability of commercial and public services in the residential location. Data relating to the accessibility of neighborhood facilities, such as living-, education-, and medical facilities, around the housing were acquired from housing agencies. The variable definitions and expected signs for housing price are presented in Table 1 and the descriptive statistics of variables are given in Table 2.

Model Specification

This study explored the heterogeneous effects of urban landscapes on the housing prices in Guangzhou, where the housing market in the whole city was divided into three housing submarkets according to the purchase motives of the homebuyers: the first-time housing, the improvement housing, and the investment housing submarket. To estimate amenity effects of the landscapes and analyze the landscape preferences of different types of buyers, eight models were established for the whole housing market and three submarkets based on the hedonic price analysis framework.

1. Basic model

   The traditional hedonic price model is regarded as a benchmark for subsequent analysis and comparison. After repeated comparisons and attempts, this study used the logarithmic hedonic price model because of its excellent fitting ability. Seven landscape variables were introduced in the models to assess the effect of urban landscapes on housing prices from the three dimensions of accessibility, visibility, and availability. Basic Models 1–4 are defined as follows:

   $$\ln P = \alpha_0 + \beta_i \ln D_i + \gamma_j V_j + \delta_k X_k + \varepsilon \qquad (1)$$

   where P=housing prices; D_i =accessibility variables of landscapes, which were adapted into logarithmic form; V_j = dummy variables to measure the visibility and availability of landscapes; X_k =other housing characteristics; α_0, β_i, γ_j, and δ_k = coefficients to be estimated; and ε=error term.

2. Quantile regression model

   The amenity effects of urban landscapes are variable across the entire distribution of housing prices (Czembrowski et al. 2016), the mean-based regression method is therefore insufficient to capture heterogeneous effects (Mcmillen 2012;

Table 2. Descriptive statistics

Variables	Mean	Standard deviation	Minimum	Maximum
Housing price (P)	2,080,000	1,720,000	500,000	20,800,000
Area (A)	89.823	43.516	22.28	476.43
Floor (F)	9.995	7.505	1	33
Top floor (TF)	0.061	0.239	0	1
Elevator (ELEV)	0.624	0.484	0	1
South (S)	0.623	0.485	0	1
Distance to hospital (DH)	2.359	2.599	0.043	36.841
Distance to subway station (DSS)	10,825	0.98	1.039	0.034
Distance to primary school (DPS)	10,825	0.805	0.621	0.021
Tianhe central business district (CBD)	10,825	0.278	0.448	0
Distance to business center (DBC)	10,825	2.064	1.583	0.107
Distance to the Pearl River (DPR)	10,825	1.999	1.63	0.052
Distance to urban park (DUP)	10,825	1.655	1.012	0.053
Garden view (GV)	10,825	0.188	0.391	0
River view (RV)	10,825	0.056	0.231	0
Landmark view (LV)	10,825	0.008	0.089	0
Proximity to viaduct (PV)	10,825	0.039	0.195	0
Proximity to road (PR)	10,825	0.133	0.34	0

Table 3. Regression results of basic models

	Whole sample (1)		First-time sample (2)		Improvement sample (3)		Investment sample (4)	
ln P	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
ln area (ln A)	1.041***	0.000	1.014***	0.000	1.059***	0.000	0.886***	0.000
Floor (F)	0.004***	0.000	0.005***	0.000	0.003***	0.000	0.003*	0.065
Top floor (TF)	−0.117***	0.000	−0.132***	0.000	−0.079***	0.000	−0.055	0.181
Elevator (ELEV)	0.228***	0.000	0.234***	0.000	0.186***	0.000	0.241***	0.000
South (S)	0.029***	0.000	0.025***	0.000	0.035***	0.000	0.008	0.667
ln distance to hospital (lnDH)	−0.115***	0.000	−0.111***	0.000	−0.118***	0.000	−0.056***	0.000
ln distance to subway station (lnDSS)	−0.033***	0.000	−0.048***	0.000	0.000	0.987	−0.042***	0.004
ln distance to primary school (lnDPS)	−0.011***	0.004	−0.002	0.716	−0.012*	0.084	−0.023*	0.087
Tianhe central business district (CBD)	0.262***	0.000	0.247***	0.000	0.264***	0.000	0.263***	0.000
ln distance to business center (lnDBC)	−0.025***	0.000	−0.019***	0.000	−0.043***	0.000	−0.031**	0.020
ln distance to the Pearl River (lnDPR)	−0.028***	0.000	−0.024***	0.000	−0.036***	0.000	−0.037***	0.001
ln distance to urban park (lnDUP)	−0.022***	0.000	−0.019***	0.000	−0.028***	0.000	−0.028*	0.054
Garden view (GV)	0.075***	0.000	0.065***	0.000	0.094***	0.000	−0.019	0.605
River view (RV)	0.052***	0.000	0.048***	0.001	0.069***	0.000	−0.008	0.882
Landmark view (LV)	0.066**	0.017	0.001	0.968	0.220***	0.000	0.031	0.716
Proximity to viaduct (PV)	−0.074***	0.000	−0.071***	0.000	−0.057**	0.018	−0.134***	0.002
Proximity to road (PR)	−0.009	0.272	−0.002	0.847	−0.020	0.165	−0.077**	0.012
Year2014	0.100***	0.000	0.095***	0.000	0.094***	0.000	0.141***	0.000
Year2015	0.075***	0.000	0.072***	0.000	0.064***	0.000	0.149***	0.000
Year2016	0.126***	0.000	0.113***	0.000	0.134***	0.000	0.220***	0.000
Constant	9.476***	0.000	9.557***	0.000	9.501***	0.000	10.102***	0.000
Number of observations	10,825	—	6,595	—	3,447	—	783	—
Adjusted R^2	0.832	—	0.803	—	0.847	—	0.772	—

Variables

Note:***, **, and * denote coefficients that are significant at 1%, 5%, and 10% significance levels, respectively.

Ebru and Eban 2011). The quantile regression model, however, provided us with a good analysis method. Koenker and Bassett (1978) introduced quantile regression in 1978. As a natural extension of the linear regression model, this model has the following two advantages. First, it relaxes the assumption of variance homogeneity in the regression model and reduces the interference of outliers, meaning the estimation result is robust. Secondly, by modeling the conditional quantile as a function of covariates, a comprehensive description of how covariates affect the distribution shape of the dependent variable can be obtained, which provided us with flexibility in studying the landscape preferences of specific groups. Therefore, this study introduced a quantile regression model as an optimization to evaluate the heterogeneous effect of landscape on houses at different prices. Models 5–8 are defined as follows:

$$\ln P = \alpha_0(\tau) + \beta_i(\tau)\ln D_i + \gamma_j(\tau)V_j + \delta_k(\tau)X_k + \varepsilon \quad (2)$$

where τ=quantile point; and $\alpha_0(\tau)$, $\beta_i(\tau)$, $\gamma_j(\tau)$, and $\delta_k(\tau)$=coefficients to be estimated.

Results and Discussion

Results of Basic Models

Table 3 (Column 1) gives the results of Model 1 for the whole sample. Nearly all variables were significant and in the expected range. As anticipated, the structure, location, and neighborhood characteristics of housing affected housing prices significantly, thereby coinciding with previous findings on the Guangzhou housing market (Jia et al. 2018). The adjusted R^2 of the model was 0.832, which indicates that more than 80% of the difference in housing prices could be explained by the model.

In Model 1, the landscape accessibility and visibility variables (distance to the Pearl River, distance to the urban park, garden view, river view, and landmark view) were significant at the 1% level, revealing that these landscape features bring a premium to surrounding housing prices. Specifically, every 1% increase in distance from the Pearl River and the nearest urban park to a house will result in a 0.028% and 0.022% decrease in the housing price, respectively. A garden view will increase the housing price by 7.8% ($e^{0.075}-1$), whereas having a river view or landmark view will bring a 5.3% and 6.8% premium, respectively. These results reflect the scarcity of the metropolitan landscape and the strong willingness of buyers to pay for beautiful landscapes (Batabyal et al. 2003). Proximity to viaducts and roads may leave property exposed to air pollution and traffic noise (Levkovich et al. 2016). Chen and Jim (2010) indicated that housing prices reduce by 1.39% if they are close to the main street. However, the results of some empirical studies have noted that people's aversion to noise is not strong in prosperous urban environments. For example, Hui et al. (2007) even found that noise level was positively correlated with housing prices, which might be attributed to the uniqueness of the dense living environment in Hong Kong where households are willing to sacrifice serenity for convenience. In the current study, proximity to viaducts incurred a negative effect on housing prices, whereas proximity to roads had no such significant effect. A viaduct within 500 m of a house will discount housing prices by 7.1%, indicating that people attach great importance to avoiding traffic noise and traffic-related air pollution.

The housing market was subdivided on the basis of homebuyer purchase motives; the OLS regression results of the three submarket samples are presented in Columns 2–4 of Table 3. By comparing the coefficients of different submarkets, a significant heterogeneous landscape preference was observed between consumption and investment homebuyers. In the two submarkets that represent consumption housing purchases, the landscape accessibility and visibility variables had amenity effects on housing prices, whereas the effect of visibility variables on the investment housing market was insignificant. In other words, whether the housing has an attractive landscape view was not an essential consideration for investment homebuyers when they purchased a house. Obviously, a mean effect resulting from whole sample analysis will be inaccurate and insufficient to describe the heterogeneity of landscape preferences; market segmentation, however, provided a more accurate picture of the amenity effect of landscapes on housing.

For consumption homebuyers (first-time and improvement homebuyers), an attractive landscape was particularly important. The accessibility of the Pearl River and the urban park, as well as visibility of a garden or river, increased housing prices significantly. Moreover, improvement homebuyers were more willing to pay extra for accessibility and visibility of high-quality landscapes compared with first-time homebuyers. Proximity of viaducts showed a significant disamenity effect in both consumption submarkets, but had a greater negative effect on the housing prices of the first-time submarket.

Compared with consumption homebuyers, investment homebuyers paid more attention to location, subway, primary school, and other housing characteristics. Landscape accessibility was also valued in the investment submarket. For example, for every 1% decrease in the distance to the Pearl River and the urban park, house prices increased by 0.037% and 0.028%, respectively, which were slightly higher than the 0.028% and 0.022% for the whole sample. Investment homebuyers were less sensitive to landscape visibility. However, for landscape proximity variables, such as proximity to viaducts and roads, investment homebuyers showed a stronger aversion, thereby causing housing price discounts to reach as high as 12.5% ($e^{-0.134}-1$) and 7.4%, respectively.

Results of Quantile Regression Models

To overcome the limitations of the traditional hedonic price model, Models 5–8 applied quantile regression to test the heterogeneous amenity effects of landscapes in the overall market and submarkets. The estimation results are given in Table 4. To explore the quantile effect of landscapes directly, we provide a complete regression estimate of the landscape variables in the Appendix (Figs. 1–4).

The results of Model 5 showed that the effects of landscapes on housing prices varied among different price quantiles in the overall housing market. The absolute value of estimated coefficients for the distance to the Pearl River indicated a significant upward trend, that is, rising from 0.018 at the 25th quantile to 0.041 at the 75th quantile, which means that the accessibility of the Pearl River had an amenity effect on housing at different price levels, and the effect was greater on high-priced houses. The premium effect of park accessibility showed a similar trend, and the implicit value of a river view was relatively stable across all housing price distributions. A landmark view exhibited a significant premium effect at high quantile points, that is, a landmark view was not a significant attraction for homebuyers of low-priced housing, however, it raised the cost of medium- and high-priced housing extensively. Proximity to viaducts had a highly negative effect on housing prices, and the discount this brought rose from 3.8% at the 25th to 7.4% at the 75th quantile. Proximity to roads only had a negative effect on low-priced houses. At the 25th quantile, an urban road within 500 m of a houses caused a discount of 2.5% in its price; this level of discount was not found in relation to medium- and high-priced houses. A possible reason is that homebuyers of medium- and high-priced houses are willing to sacrifice tranquillity for a better location and convenience. These results indicated that buyers of different classes had heterogeneous landscape preferences and demands.

The regression results of Models 6–8 provided in Table 4 describe the heterogeneity of landscape values in the submarkets across different conditional distributions of housing prices. In the consumption demand housing market (Models 6 and 7), the effect of accessibility to the Pearl River was on the rise across the whole housing price distribution, and buyers with improvement demands were more willing to pay for the Pearl River landscape. The effect of urban parks showed the opposite trend in the two submarkets. In the first-time submarket, high-priced housing was affected more by parks, while in the improvement submarket, low-priced housing was greatly affected. In addition, the implicit value of landscape features was relatively stable across the entire distribution of the improvement submarket, and this value tended to be higher than those of other submarkets. This phenomenon may be due to the fact that improvement homebuyers have the financial strength to select communities with more complete facilities. The landmark landscape coefficients were significant with the expected signs, indicating that wealthy people prefer city landmark views. In the investment submarket, homebuyers who chose mid- to high-priced housing had a stronger willingness to pay for accessibility to the Pearl River and parks while also avoiding the negative impact of unattractive facilities.

The proceeding analysis indicated that the traditional model based on OLS regression will over- or underestimate the effects

Table 4. Regression results of quantile regress models

Variables	Whole sample (5)			First-time sample (6)			Improvement sample (7)			Investment sample (8)		
ln P	q25	q50	q75	q25	q50	q75	q25	q50	q75	q25	q50	q75
ln area (ln A)	0.995***	1.061***	1.085***	0.952***	1.013***	1.082***	1.053***	1.096***	1.079***	0.812***	0.876***	0.959***
Floor (F)	0.005***	0.004***	0.003***	0.006***	0.005***	0.004***	0.004***	0.003***	0.002**	0.005**	0.001	0.002
Top floor (TF)	−0.140***	−0.118***	−0.107***	−0.151***	−0.132***	−0.115***	−0.074***	−0.085***	−0.120***	−0.033	0.030	−0.029
Elevator (ELEV)	0.258***	0.250***	0.218***	0.249***	0.256***	0.227***	0.228***	0.191***	0.166***	0.283***	0.307***	0.224***
South (S)	0.026***	0.036***	0.028***	0.012	0.027***	0.028***	0.042***	0.049***	0.014	−0.001	0.005	0.018
ln distance to hospital (lnDH)	−0.105***	−0.119***	−0.108***	−0.099***	−0.114***	−0.113***	−0.104***	−0.117***	−0.131***	−0.051***	−0.055***	−0.058***
ln distance to subway station (lnDSS)	−0.067***	−0.051***	−0.005	−0.085***	−0.075***	−0.037***	−0.032***	0.008	0.035***	−0.035**	−0.041**	−0.014
ln distance to primary school (lnDPS)	−0.007	−0.012**	−0.006	0.009*	0.005	0.005	−0.021**	−0.021**	−0.004	−0.043***	−0.038**	0.002
Tianhe central business district (CBD)	0.245***	0.272***	0.268***	0.208***	0.228***	0.270***	0.281***	0.269***	0.243***	0.266***	0.256***	0.241***
ln distance to business center (lnDBC)	−0.007	−0.026***	−0.053***	−0.003	−0.016***	−0.034***	−0.021**	−0.048***	−0.063***	−0.011	−0.024	−0.055***
ln distance to the Pearl River (lnDPR)	−0.018***	−0.031***	−0.041***	−0.012***	−0.026***	−0.040***	−0.034***	−0.042***	−0.047***	−0.037***	−0.034***	−0.055***
ln distance to urban park (lnDUP)	−0.019***	−0.031***	−0.042***	−0.011**	−0.023***	−0.043***	−0.043***	−0.035***	−0.030***	−0.036**	−0.044**	−0.024
Garden view (GV)	0.053***	0.087***	0.065***	0.041***	0.063***	0.054***	0.094***	0.114***	0.084***	−0.011	−0.034	0.016
River view (RV)	0.047***	0.040***	0.042***	0.023	0.016	0.043*	0.086***	0.059***	0.070***	−0.075	−0.043	0.040
Landmark view (LV)	−0.012	0.065*	0.140***	−0.062	0.025	0.030	0.159**	0.279***	0.253***	0.060	0.038	0.011
Proximity to viaduct (PV)	−0.039**	−0.081***	−0.077***	−0.054***	−0.065***	−0.074***	−0.050	−0.082***	−0.073**	−0.094*	−0.114**	−0.116*
Proximity to road (PR)	−0.025**	0.000	−0.007	−0.030**	0.004	0.009	−0.040*	−0.014	−0.002	−0.036	−0.082**	−0.092**
Year2014	0.096***	0.083***	0.110***	0.088***	0.082***	0.109***	0.077***	0.077***	0.109***	0.138***	0.140***	0.164***
Year2015	0.077***	0.058***	0.075***	0.072***	0.056***	0.080***	0.059***	0.040***	0.02***	0.075**	0.153***	0.174***
Year2016	0.113***	0.114***	0.156***	0.101***	0.113***	0.138***	0.112***	0.105***	0.167***	0.156***	0.240***	0.245***
Constant	9.471***	9.371***	9.503***	9.649***	9.547***	9.461***	9.300***	9.341***	9.670***	10.200***	10.100***	10.020***
Number of observations	10,825	10,825	10,825	6,595	6,595	6,595	3,447	3,447	3,447	783	783	783

Note: ***, **, and * denote coefficients that are significant at 1%, 5%, and 10% significance levels, respectively.

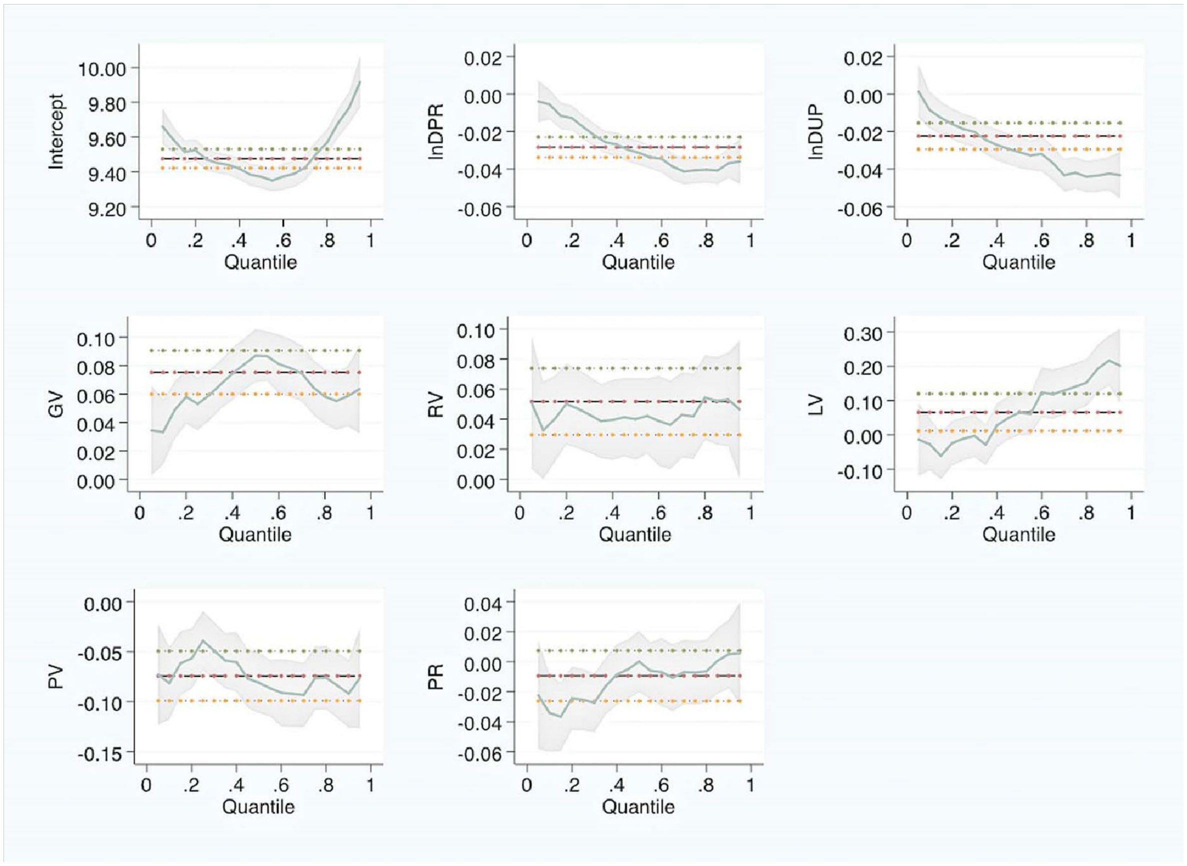
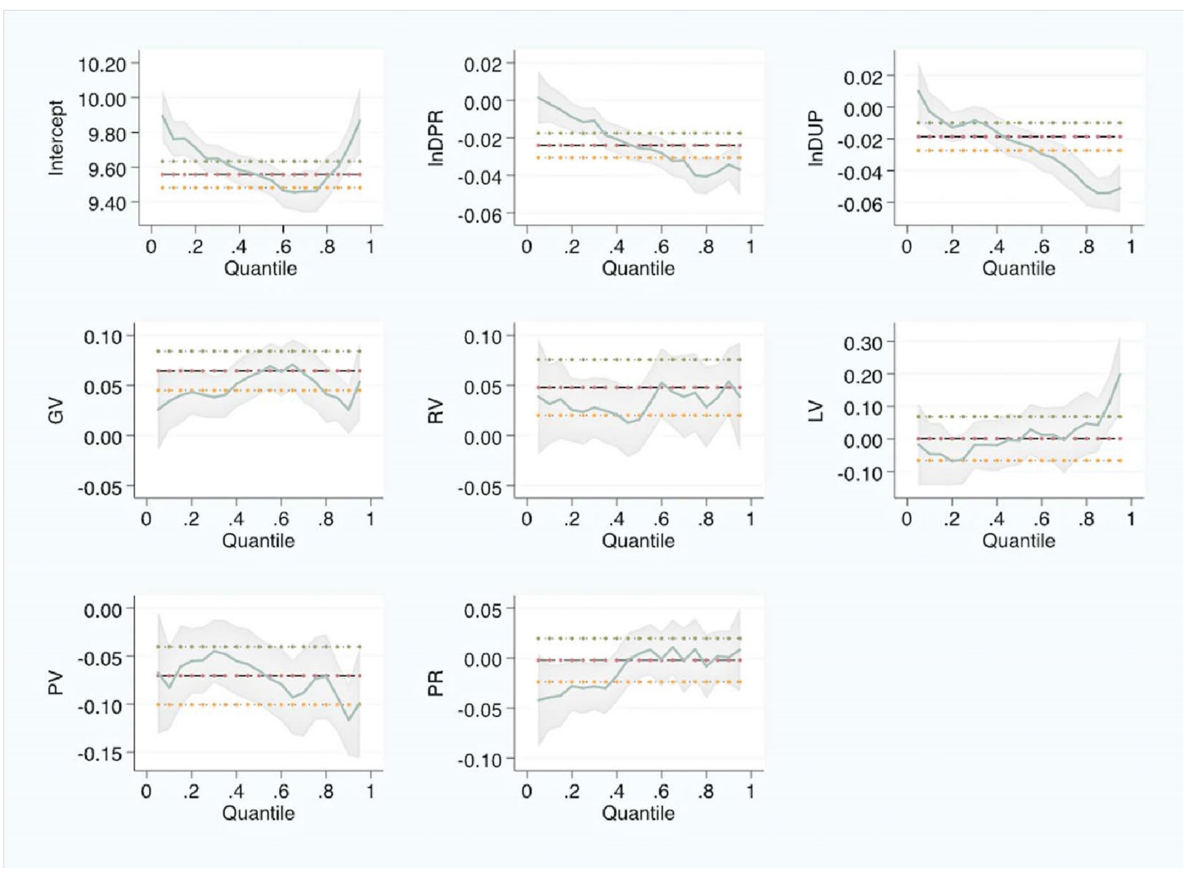


Fig. 1. Quantile regression results of the whole sample.



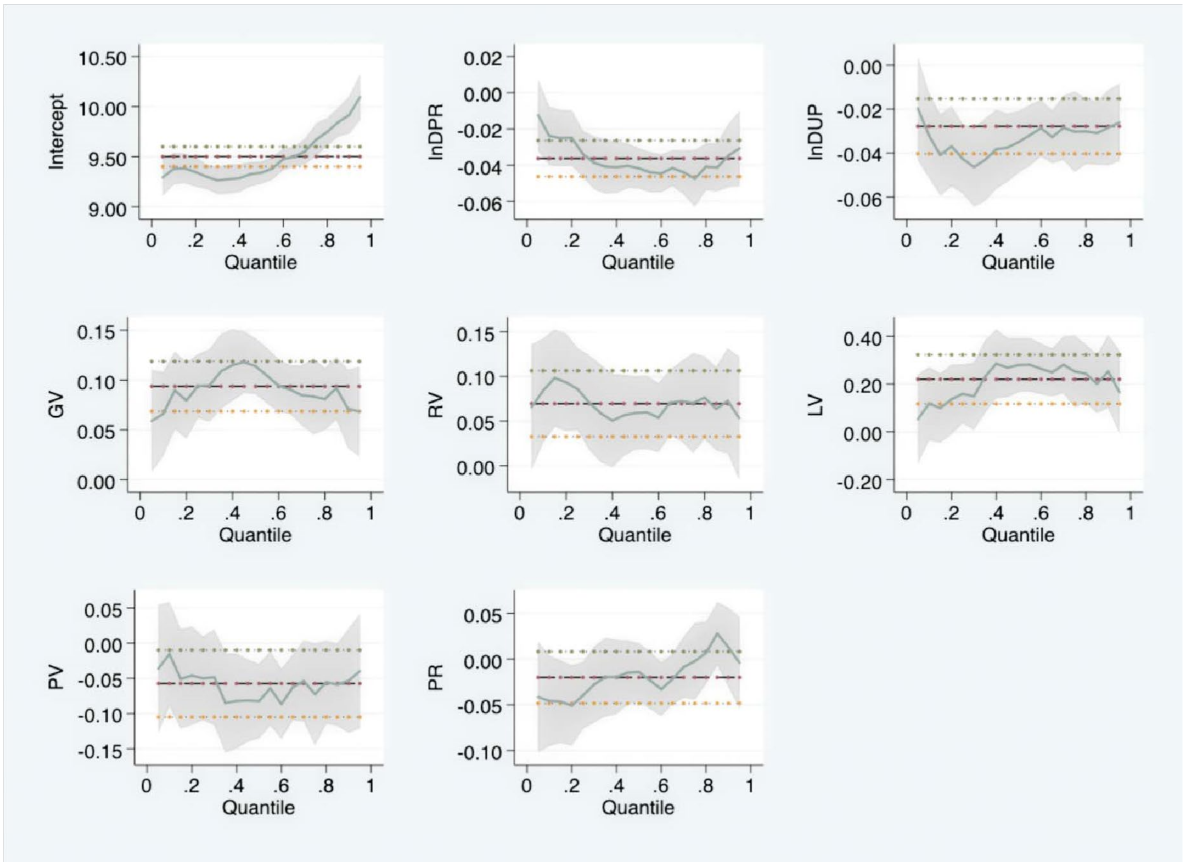


Fig. 2. Quantile regression results of the first-time sample.

Fig. 3. Quantile regression results of the improvement sample.

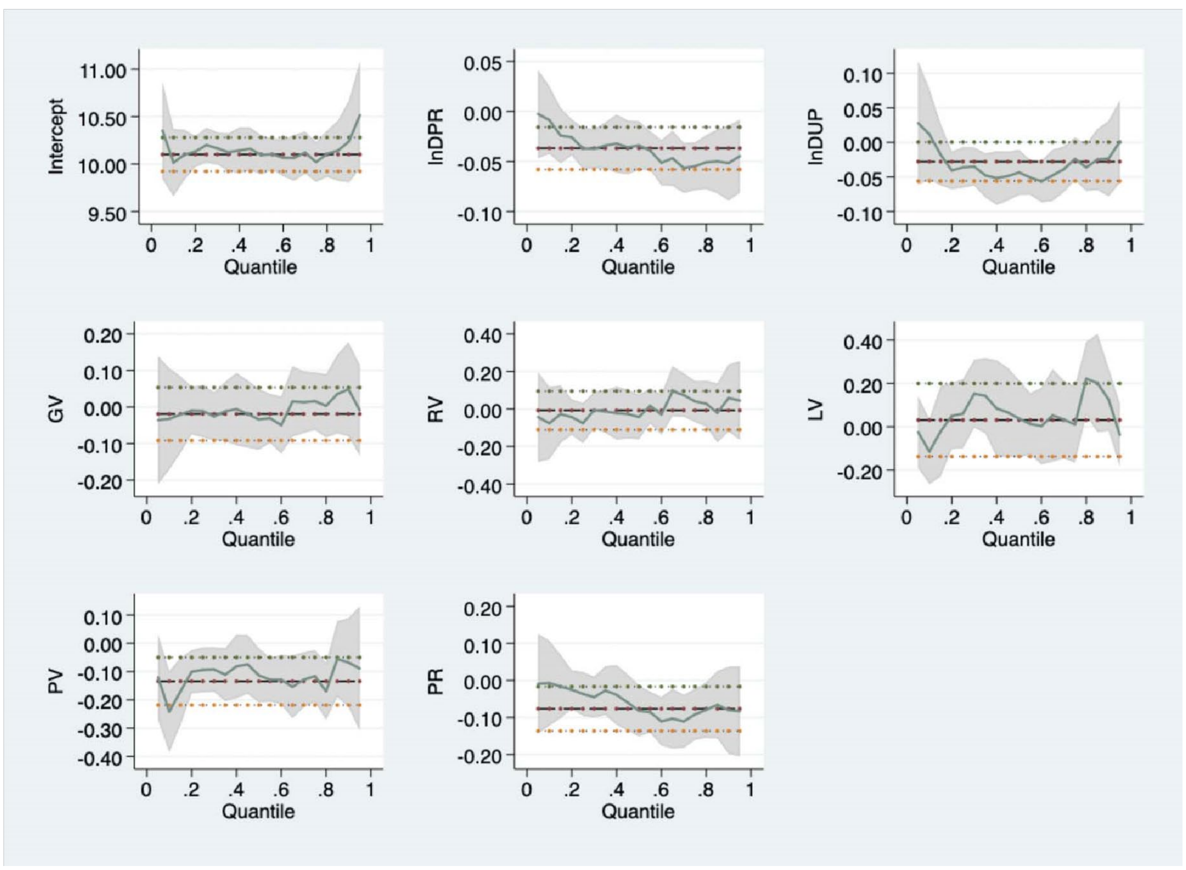


Fig. 4. Quantile regression results of the investment sample.

of landscapes on housing prices. First-time homebuyers paid more attention to whether their funds could buy a house with good structural characteristics, convenient transportation links, and an attractive environment. In the improvement housing submarket, homebuyers were relatively more affluent and preferred a better location and a more attractive environment compared with first-time homebuyers. They were in a financial position to choose a house with a high-quality landscape view and were willing to pay the corresponding price. In addition, the quantile effects of landscapes changed more drastically in the first-time market, but were stable in the improvement housing market. This finding can be explained by the fact that the economic conditions of first-time homebuyers are quite different: wealthy people are in a position to pay higher prices for high-quality landscapes, but improvement buyers have a similar willingness to pay for landscapes, which is usually higher than first-time buyers. Investment homebuyers tended to attach importance to the premium of housing space. When they made a purchase decision, they focused on the rental income and the future value-added space of the housing, which is often closely related to neighborhood and location factors. At the same time, they paid more attention to whether there were unattractive facilities in the vicinity of the house that might affect its appreciation.

Conclusions

Although concerns about the amenity effect of urban landscapes continue to rise, existing literature rarely focuses on the heterogeneity of the landscape preferences of homebuyers in housing submarkets. To fill this gap, this study took Guangzhou as an example, a typical city in China, subdivided the housing market according to the purchase motivation of homebuyers, and explored the average and quantile effects of different types of landscapes on housing prices. On this basis, we further analyzed the differences in landscape preferences between consumption- and investment demand homebuyers and drew the following conclusions:

1. In general, various types of urban landscapes have significant effects on housing prices. Seven landscape variables, including distance to the Pearl River, distance to urban park, garden view, river view, landmark view, proximity to viaduct, and proximity to road, were selected from the three dimensions of accessibility, visibility, and availability. On average, for every 1% reduction in distance to the Pearl River or park, housing prices rose by 0.028% and 0.022%, respectively; owning a garden, river, and urban landmark view brought a 7.8%, 5.3%, and 6.8% premium to houses, respectively. Proximity to viaducts decreased the prices of the surrounding houses by 7.1%, but proximity to roads had an insignificant impact on housing prices. With people′s emphasis on environmental quality, this finding shows that buyers are willing to pay a premium to obtain a high-quality and attractive landscape. At the same time, adjacent viaducts and roads have a negative impact on housing prices because of possible air pollution and traffic noise.
2. From the perspective of the housing submarkets, different types of homebuyers have substantially different landscape preferences. Landscape accessibility and visibility had significant effects on housing prices in the consumption housing market. Compared with first-time buyers, improvement buyers usually have more abundant funds and are able to pay higher prices for housing adjacent to beautiful urban landscapes. Investment homebuyers, however, showed a stronger aversion to adjacent viaducts and roads, that is, they were more sensitive to the negative effects of unattractive landscape facilities that may affect the appreciation of housing. Evidently, analyzing the sample as a whole to describe the heterogeneous landscape preferences of homebuyers with different purchase motives is difficult, and housing market segmentation enabled us to portray landscape effects more accurately.
3. Substantial differences in the quantile effect of landscapes were revealed across different conditional distributions of housing prices. Buyers who purchased high-priced houses were more willing to pay for attractive landscapes than those who bought low-priced houses; they were also willing to pay higher prices to avoid the negative effects of viaducts and other unattractive landscape features. The quantile regression model obtained more detailed results that clearly described the behavioral differences of high- and low-end housing homebuyers.

These empirical results showed that the relationship between landscape effect and housing prices is complicated in housing submarkets differentiated by purchase motivations. The results of this study should be addressed against a background of investment and consumption demand coexistence in the Chinese housing market. Some suggestions follow. First, with the improvement in urban-living standards, the demand for high-quality environments has intensified, and the amenity value of garden-, river-, and landmark views has been converted into housing prices. The findings of this study could prove valuable for developers in determining the tastes and preferences for landscape facilities in relation to buyers with different housing demands and income levels; the data could improve project planning. Second, in the design and evaluation of public policies, the relationship between local public goods and the housing market should be fully considered. The layout should be uniform and reasonable when planning the urban landscape so that residents of different classes can enjoy the amenities as equitably as possible, avoiding the social problems caused by the excessive occupation of high-income groups. In addition, when planning unattractive urban facilities, relevant compensation mechanisms could be established to reduce the negative effects on surrounding housing prices. Finally, these results could help investors and homebuyers to place reasonable emphasis on housing facilities to optimize consumption or investment returns.

There were some limitations to this study. Substantial differences exist in the demand structure of housing markets in different cities. However, this study only investigated Guangzhou; further research should expand the coverage of cities. In terms of privacy protection, the housing data obtained from real estate agencies did not contain accurate spatial information; future research could use spatial econometric methods to improve model estimates and to control the effects of spatial dependence.

Appendix. Quantile Regression Estimates of Landscape Variables

To visually and clearly explore the quantile effects of landscape in different housing submarkets, we provide a complete regression estimate of landscape variables with a quantile of 0.05 increments (Figs. 1–4).

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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