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Residents' Demands for Urban Retail: Heterogeneity in Housing Structure Characteristics, Price Quantile, and Space

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Abstract: A thorough understanding of residents' demands plays an important role in realizing the rational distribution of urban retail (*UR*) and promoting the habitability of cities. Unfortunately, these demands for *UR* are currently under-researched. To solve this problem, this study aims to quantify the capitalization effect of *UR* on housing prices and explores the impact of heterogeneity in housing structure characteristics, price quantile, and space on the residents' demands for *UR* according to the hedonic price model, quantile regression, and geographically weighted regression in Chengdu. The results of these models show the following: (1) good property management and building sound insulation can reduce the negative influence of *UR* on residents' lives; (2) only the owners of low-price houses are willing to pay a premium for *UR*; and (3) residents' demands for *UR* increase from the central area to the peripheral area of Chengdu, and an inverted U-shaped relationship was found between housing prices and the *UR* level. A comprehensive analysis of the heterogeneity of residents' demands for *UR* can provide a reference for planning departments, real-estate developers, and *UR* owners and promote the sustainable development of *UR*.

Keywords: housing price; urban retail; residents' demands; hedonic price method; quantile regression; geographically weighted regression

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1. Introduction

There is an increasing integration of commercial activities in the marketplace, and the term urban retail (*UR*) refers to all consumer-related activities, including the following categories: shopping for personal and household goods and services; dining out; engaging in recreation; and attending sports, entertainment, and cultural events [1]. Many studies, while only adopting *UR*-related variables as control variables, have confirmed *UR* to be an important determinant for residents' expected housing prices [2–5]. The results of these studies showed positive and negative effects on housing prices simultaneously. This phenomenon may be caused by the double impact on residents' welfare and quality of life.

On the one hand, *UR* has a positive impact on residents' welfare and quality of life. The development of urban retail plays an increasingly important role in improving urban economic performance and residents' welfare. At the urban level, *UR* can also drive the production activities of other sectors, improve the urban employment rate [6], promote the construction of urban support infrastructure, and optimize urban planning and layout [7,8]. In terms of residents' quality of life, an improvement in *UR* improves the accessibility and availability of commercial services [9], which help meet residents' growing entertainment demands as a consequence of an increase in their incomes [8,10], while simultaneously reducing their travel time and costs [11,12]. These positive impacts provide the positive capitalization effect of *UR* on housing prices and lead to increased residents' demands for *UR*.

On the other hand, *UR* has negative effect on residents' welfare and life quality. Increased *UR* density would lead to a massive influx of people and vehicles into a region, which could lead to severe noise and air pollution, garbage, more congested roads [9,10,13], and an increase in crime rates [14]. As a result, an increase in *UR* has a negative effect on housing prices and can reduce residents' demands for *UR*, pushing some residents to even reject *UR*.

Furthermore, because of the heterogeneity in housing structure characteristics, price quantile, and space, different residents may have different attitudes towards the negative and positive impacts of *UR* and have different demands degree and expected prices on *UR*. Previous studies have supported this argument for other public services or infrastructure. However, few studies have focused on *UR* [14–16]. Therefore, analyzing the capitalization effect of *UR* on housing prices and further exploring the residents' demand for *UR* in heterogeneous conditions (housing structure characteristics, price quantile, and space) are important and interesting issues to explore.

In this study, we assume that residents' demands for *UR* are primarily impacted by heterogeneity in housing structure characteristics, price quantile, and space. In other words, the capitalization effect of *UR* on housing price is not constant. This study helps answer the following questions:

(1) How are the capitalization effects of *UR* on housing prices and residents' demand for *UR* affected by heterogeneity in housing structure characteristics, price quantile, and space?
(2) How should the *UR* layout of the city based on heterogeneity in housing structure characteristics, price quantile, and space be adjusted?

The answers to the above questions can provide a reference for the government's urban planning decisions and the formulation of housing development targets by real-estate developers. To answer these questions, this study aims to quantify the capitalization effect of *UR* on housing prices by using the hedonic price model, quantile regression, and geographically weighted regression based on second-hand housing transaction data from a Chengdu real-estate intermediary website in 2019 and to further examine residents' demands for *UR* in heterogeneous conditions.

The remainder of this paper is organized as follows. Section 2 summarizes the relevant studies. Section 3 introduces the research data and methods. Section 4 presents the main results and discusses them. Section 5 summarizes the study's conclusions, practical implications, and limitations.

2. Literature Review

Housing prices are closely related to cities' development and residents' quality of life. According to the hedonic price model, scholars base housing prices on several implicit housing characteristics and explore residents' demands for those housing characteristics. Previous studies have divided these characteristics into three categories: (1) structural characteristics, such as the age of the house [17], size, floor [16], and orientation [18]; (2) location characteristics, such as education resources [19], transportation [2], and landscape [20]; and (3) environmental characteristics, such as noise [21], afforestation [3], crime rate [22], and pollution [23]. *UR* is an integral component of urban vitality and residents' lives and has a significant impact on housing prices. However, its impact is seldom discussed in the literature.

In many studies, *UR*-related factors have been employed as control variables [2–5]. These results are significantly different and show negative and positive capitalization effects of *UR* on housing prices, while simultaneously suggesting potential and different residents' demands for *UR* in heterogeneous conditions. In recent years, some scholars have begun to focus on the capitalization effect of *UR*-related factors. Song et al. [1] have discussed the premium of retail accessibility on housing prices. Yu et al. [24], Sirpal [25], and Sale [26] have investigated the impact of shopping mall accessibility on housing prices. Some have contended that considering the relationship between *UR* and housing prices solely based on accessibility is inappropriate since the nearest *UR* center is not the only choice available to customers [27]. They may shop elsewhere on their way to work or anywhere else "as long as it suits their lifestyle" [28]. Jang and Kang [9] have examined the gap of the relationships between housing prices and different retail stores such as department stores, shopping centers, hypermarkets, supermarkets, and convenience stores. Zhang et al. [13] have classified shopping malls according to the size, age, and structure of the tenants and discussed the influence of different types of malls on housing prices. Chiang et al. [14] studied the impact of convenience stores on housing prices from the perspective of density and availability in Taipei city. As more *UR* stores provide more choices for consumers in accordance with their different lifestyles, this study analyzes the residents' demands for *UR* based on the number of *UR* stores surrounding houses. This is the first study to undertake such an investigation.

Previous studies have found that the capitalization effect of *UR* and residents' demands for *UR* are not constant. Song and Sohn [1] previously investigated the impact of retail accessibility on housing prices. The positive impact of retail channels on housing prices was found to decrease rapidly with distance. Simultaneously, when the distance between retail stores and the house is reduced to a certain level, a further reduction in distance decreases housing prices. Some scholars have obtained similar results for the impact of shopping malls' accessibility on the externalities of housing prices [10,13,25,26,29], and have attributed the results to the spatial distribution [13] and two-way influence of *UR*: increasing convenience in the residents' lives and the damage to the environment (noise, traffic congestion, and pollution) [29]. The negative influence of *UR* on the comfort of residents' lives may be the core reason for the negative effect of *UR* on housing prices. Hence, reducing residents' perceptions of the adverse influence on the environment (for instance, by increasing sound insulation capacity through better construction technology) may have a positive impact on their demand for *UR*. Generally, the heterogeneity of housing structure characteristics may have a moderating effect on the residents' demands. This has been confirmed in some studies that focus on other factors. For example, Xiao et al. [16] explored the moderating effect of vertical heterogeneity at different floor levels on the residents' demands for landscape. Liu et al. [30] also confirmed that community population density can reduce the negative influence of COVID-19 on housing prices. Li et al. [31] analyzed the moderating effects of built-environment factors on rail transit proximity premiums. However, few studies have discussed the moderating effects of housing structure characteristics on the residents' demands for *UR*. This study aims to address this gap.

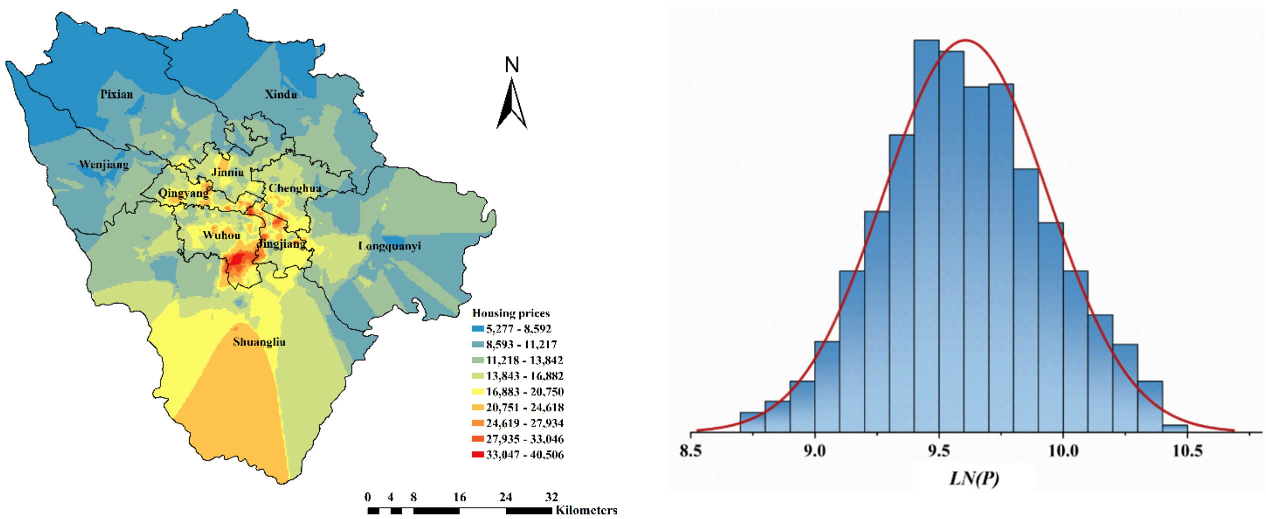
For the price quantile effect, the residents' income levels and total assets largely determine their demands. Bayer [32] has provided empirical evidence on families from different social classes and indicated that the marginal willingness to pay increases with income. This effect cannot be observed directly using a traditional hedonic price model [33]. Many scholars have adopted quantile regression because it provides a comprehensive estimate of the entire housing price distribution based on different regression curves [34]. Based on Hong Kong's housing market, Mak et al. [35] have confirmed a substantial difference in the preferences of owners of houses with different values. Wen et al. [36] found that residents' demands for educational resources (such as the presence of a primary school, middle school, and college) differ across quantiles in Hanzhou (China). The owners of high-price houses represented higher presence for a college and a high school. Using Quantile Regression, Chiang et al. [14] noted that the regression coefficients on convenience store density show a non-linear trend, revealing a positive effect in low-price communities and an inhibiting effect on high-price neighborhoods. Wang [37] combined the spatial and the quantile regression approach and found the influence of the subway on all levels of housing rents to be negligible. In addition, some scholars have studied the quantile effects of other characteristics on housing prices, such as wildfire likelihood [38], household attributes [39], flood risk [40], tourism [41], and natural environment features [42]. However, the quantile effect is rarely considered in studies investigating the capitalization effect of *UR* on housing prices and identifying the residents' demands for *UR* in heterogeneous housing structure characteristics, heterogeneous price quantile, and heterogeneous space.

This study makes an important contribution to the literature. In contrast to previous research, this study is the first to use the number of *UR* stores as a *UR*-related variable and consider the heterogeneity of housing structural characteristics, price quantile, and space to study the capitalization effect of *UR* on housing prices and residents' demands for *UR*.

3. Materials and Methods

3.1. Study Area

Chengdu, the capital of Sichuan province, is the study area. Chengdu is one of the political, financial, and transportation centers of Southwest China and had a GDP of 1700 billion yuan and a population of 16 million in 2019 [43]. The exciting culture, pleasant environment, and abundant presence of historical sites attract a large number of tourists to Chengdu every year. The solid economic foundation and the developed tourism industry have promoted *UR* development in Chengdu. The study area includes nine municipal districts of Chengdu: Wuhou, Qingyang, Shuangliu, Qingyang, Wenjiang, Pidu, Longquanyi, and Jinniu (Figure 1a).



(**a**) (**b**)

Figure 1. Study area and housing price distribution. (**a**) the spatial distribution of housing prices; (**b**) the normal distribution of logarithm of house prices.

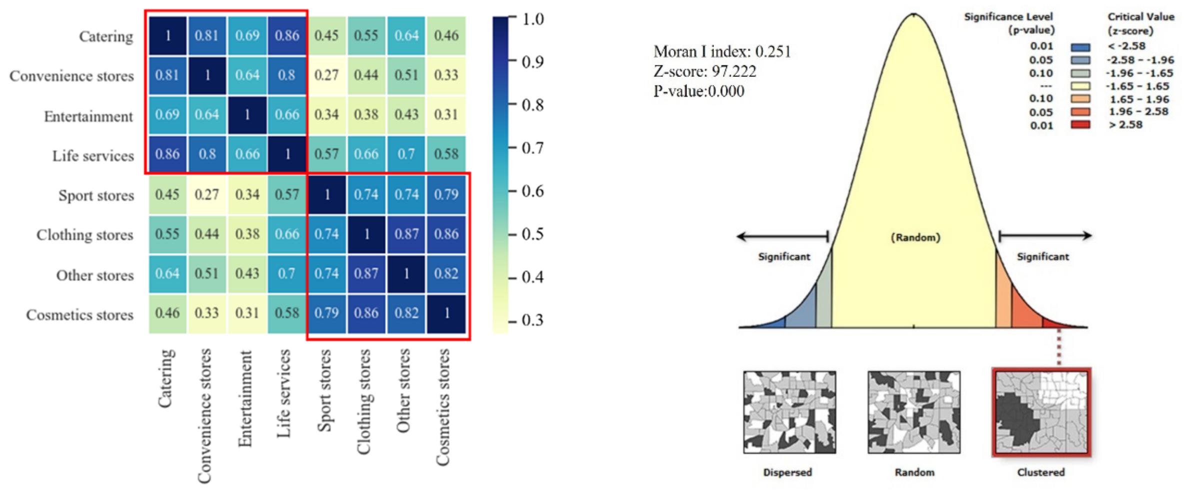
3.2. Data and Variables

3.2.1. Dependent Variables

As the second-hand housing market exhibits a considerably more dispersed and large-scale housing supply compared with the new housing market [44], this study obtains second-hand house transaction data from Fangtuanxia (fangtianxia.com), one of the largest house intermediary platforms in China. This dataset reports information regarding housing prices, housing size, the presence of elevators, the floor area ratio, and the level of property management. To make the data comparable, this study does not consider villas and town-houses, which command an obviously high housing price and only account for 2.3% of the total samples and selects the multi-layer and high-rise housings as the major research object. In addition, differences within a residential community are ignored, and the data of houses attributed to the same community are merged [45]. Therefore, the average housing prices of residential neighborhoods are used as the dependent variables. After the above treatment and removing abnormal values, the final dataset includes 73,889 houses and 2286 residential communities. The Kriging method [46] is used for the spatial interpolation of housing prices. The results are split into nine levels based on the Jenks classification. Figure 1a represents the spatial distribution of Chengdu housing prices, which is characterized by a circular distribution. The housing prices decrease from the city center to the city boundaries; the highest housing prices are in the city center area, and lower price houses are mainly distributed in Northwest Chengdu. The housing prices of Tianfu New District show a rapid growth trend due to policy support. The housing prices of Chengdu have begun to shift from a unipolar distribution centered on Tianfu Square to a bipolar distribution. In addition, the logarithm of Chengdu housing price ($LN(P)$) is approximately normally distributed (Figure 1b), and the mean of $LN(P)$ is 9.61.

3.2.2. Independent Variables

Urban retail refers to all consumer-related activities. Based on the classification rules of the Gaode Map, this study selected eight urban retail store categories, including catering stores, convenience stores, entertainment stores, life services stores, sport stores, clothing stores, cosmetics stores, and other stores (Figure 2a), and uses a number of these stores within 500 m of the house. Meanwhile, mega markets (e.g., shopping malls) are broken up into multiple independent urban retail stores, to be counted separately.



(**a**) (**b**)

Figure 2. Pearson coefficients and Moran I Index of *UR*. (**a**) represents the Pearson correlation coefficient among different urban retail types; (**b**) represents the Moran I index of urban retail.

A correlation analysis (Figure 2a) reveals that the different *UR* types are significantly correlated, and all the correlations are positive (most values exceed 0.4). Catering, clothing stores, and other stores are strongly correlated with almost all other *UR* types. In addition, there are two clusters: (1) catering, convenience stores, entertainment, and life services, and (2) sport stores, clothing stores, other stores, and cosmetics stores. When the *UR* density of an area reaches a certain level, the area may be considered a commercial area. Meanwhile, the Moran I index of *UR* is 0.251 and is significant at the 95% level (Figure 2b), which indicates a space-clustered distribution of *UR*. Furthermore, excessive correlation generates multicollinearity in the regression analysis. Therefore, the total number of stores of different *UR* types is used as a *UR*-related variable.

For control variables, consumers' demands for the functional characteristics of a house affect their willingness to pay [36]. Therefore, based on past research and residents' demands, we employ control variables from six dimensions (housing structural characteristics, education, transport, medical, environment, and others). Independent variables are divided into structural variables, surrounding variables, and environmental variables [47]. Property management (*PM*) and school district (*SD*) are the scores assessed by real estate agency websites (Fangtianxia). The assessment of property management follows the standard of property management service grade of residential building, which classifies property management into four grades depending on the degree of building management, maintenance of shared facilities and equipment, maintenance of public order, and cleaning services. The assessment of school districts is decided by the rank of the supporting primary school and junior middle school of the house. A higher number indicates a better quality of property management and school district. The distances between houses and independent variables may take two forms: real distances (in the road network) and Euclidean distances. Among them, the distances to senior high school (*DSHS*), university (*DUN*), subway station (*DSUB*), hospital (*DHOS*) and park or square (*DG*) are real distances. The distance to the urban center (*DUC*) is based on Euclidean distance; *DUC* is not used in this study to describe the accessibility of the facility but the location of houses. Table 1 lists the community-level independent housing variables and relevant descriptions.

Table 1. Independent variables and descriptions.

Category	Variable	Abbreviation	Description
Dependent variable	Residential housing prices	*P*	Price per square meter (yuan/m^2)
Structural variables	Size	*SIZE*	Area of structure (m^2)
	Year	*YEAR*	The age of the house
	Elevator	*EL*	If the residence is equipped with elevator, 0 = no; 1 = yes
	Plot ratio	*PR*	Floor Area Ratio/Volume Fraction (%)
	Property management	*PM*	0 = Needs improvement; 1 = Low; 2 = Mid; 3 = High
Location variables	Urban Retail	*UR*	The number of relevant stores within 500 m
	School district	*SD*	0 = Low; 1 = Mid; 2 = High
	Kindergarten	*KG*	The number of kindergartens within 1000 m
	Distance to senior high school	*DSHS*	The real distance (not Euclidean distance) to the nearest public senior high school
	Distance to university	*DUN*	The real distance (not Euclidean distance) to the nearest university
	Bus station	*BUS*	The number of bus stations within 500 m
	Distance to subway station	*DSUB*	The real distance (not Euclidean distance) to the nearest subway station
	Distance to hospital	*DHOS*	The real distance (not Euclidean distance) to the nearest comprehensive hospital
	Distance to urban center	*DUC*	The distance (Euclidean distance) to Tianfu Square
Environment variables	Distance to park or square	*DG*	The real distance (not Euclidean distance) to the parks or squares

3.3. Methods

The hedonic price model is typically used to analyze the relationships between housing prices and housing characteristics. It may take different forms: linear, semi-log, and log–log. No theory determines the choice of the functional form. A previous study suggests that log-form models reduce heteroscedasticity [48]. In this study, the discrete variables (*EL*, *YEAR*, *PM* and *SD*) adopt the original form, and other variables are logarithmized (Equation (1)).

$$LN(P) = \beta_0 + \beta_1 LN(UR) + \beta_4 LN(S) + \beta_5 LN(L) + \beta_6 LN(E) + \beta_7 Z + \varepsilon \quad (1)$$

where P indicates housing prices, *UR* is the *UR* level surrounding the house, β indicates the regression coefficient, S comprises continuous structural variables, L indicates continuous location variables, E comprises continuous environment variables, Z indicates other continuous-discrete variables, and ε is the error term.

In Chinese, the design of urban residential buildings must follow the standards of sound insulation. These standards of sound insulation have been revised many times to improve sound insulation performance. For example, non-standard before 2000, codes for sound insulation design of residential buildings were introduced in 2010 and 2020. Therefore, we assume building age has a positive relationship with building performance of sound insulation and use *YEAR* to characterize building performance of sound insulation. The interaction items ($LN(UR) \times PM$, $LN(UR) \times YEAR$) are introduced in the model to explore the moderating effect of housing structural characteristics (Equation (2)).

$$\begin{aligned} LN(P) = {} & \beta_0 + \beta_1 LN(UR) + \beta_2 (LN(UR) \times PM) + \beta_3 (LN(UR) \times YEAR) \\ & + \beta_4 LN(S) + \beta_5 LN(L) + \beta_6 LN(E) + \beta_7 Z + \varepsilon \end{aligned} \quad (2)$$

Quantile Regression is used to test the residents' demands on *UR* from price quantile. Quantile Regression estimators are calculated based on asymmetric absolute residual minimization. Compared with the hedonic price model, quantile regression has some advantages: (1) it does not require strong assumptions for the error terms and the estimation results are robust to outliers; and (2) it describes the whole conditional distribution of explained variables more comprehensively [36]. The regression coefficients across different housing price levels are obtained as follows:

$$LN(P) = \beta_{0(q)} + \beta_{1(q)} LN(UR) + \beta_{4(q)} LN(S) + \beta_{5(q)} LN(L) + \beta_{6(q)} LN(E) + \beta_{7(q)} Z + \varepsilon \quad (3)$$

where q indicates housing price quantiles; $\beta_{0(q)}, \beta_{1(q)}, \beta_{4(q)}, \beta_{5(q)}, \beta_{6(q)}$ and $\beta_{7(q)}$ are the qth quantile coefficients to be estimated; and the remaining variables are the same as in Equation (1).

An urban housing market, which usually comprises various submarkets, is too complex to be described as a spatially homogeneous unit [13,49]. Tobler's First Law of Geography indicates that there are more similarities between adjacent geographical entities. Due to the uneven distribution of urban retail resources and other housing characteristics, there may be spatial heterogeneity in the resident's demands for *UR*. The global regression of the hedonic pricing model is not detailed enough to explain the local conditions. The geographically weighted regression model uses the local smooth processing method to solve the problem of spatial heterogeneity. Considering spatial heterogeneity, geographic coordinates and core functions are utilized to carry out local regression estimation on the adjacent individuals of each group. Therefore, this study tests the spatial heterogeneity of the capitalization effects of *UR* on housing prices based on the result of the geographically weighted regression model, as follows:

$$LN(P_i) = \sum_j \beta_{ij}(\mu_i, v_i) X_{ik} + \varepsilon_i \quad (4)$$

where (μ_i, v_i) indicates the spatial location of sample house i, and $\beta(\mu_i, v_i)$ is the regression coefficient on sample house i. In contrast with the hedonic price model, a weighted matrix W_i is used to indicate the influence of different observation points with different spatial locations on the estimation of the coefficient of sample house i [50]. In this study, we use the Gaussian function to calculate the weighted matrix, as follows.

$$W_{ij} = e^{-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2} \quad (5)$$

where d_{ij} indicates the Euclidean distance from sample house i to observation house j, b indicates the bandwidth, and the selection of b follows the AICc criterion [50].

4. Results and Discussion

4.1. Hedonic Price Model Results

Table 2 represents the baseline hedonic price model results for the capitalization effect of *UR* on housing prices in all districts. Model (2) introduces the two interaction items. All the adjusted R^2 values exceed 0.5, indicating that the model explains over 50% of the variation in housing prices. Most regression coefficients are significant at the 5% level. Hence, the proposed hedonic price model has adequate explanatory power.

Table 2. Baseline hedonic price model results.

Variable	Model (1)				Model (2)			
	Coefficient	**SE**	***p* Value**	**VIF**	**Coefficient**	**SE**	***p* Value**	**VIF**
LN(*UR*)	−0.051 ***	0.009	0.000	1.897	−0.053 ***	0.008	0.000	1.985
LN(*UR*)×*PM*					0.020 **	0.013	0.092	2.357
LN(*UR*)×*YEAR*					−0.003 **	0.002	0.042	2.357
PM	0.085 ***	0.011	0.000	2.927	0.083 ***	0.012	0.000	3.003
YEAR	−0.014 ***	0.001	0.000	3.745	−0.014 ***	0.001	0.000	3.755
EI	0.080 ***	0.014	0.000	2.108	0.081 ***	0.014	0.000	2.128
LN(*BUS*)	0.051 ***	0.016	0.002	2.491	−0.035 ***	0.006	0.002	2.492
LN(*DSUB*)	−0.036 ***	0.006	0.000	1.227	−0.035 ***	0.006	0.000	1.233
LN(*DUC*)	−0.279 ***	0.008	0.000	1.881	−0.281 ***	0.008	0.000	1.917
LN(*DG*)	0.004	0.006	0.478	1.190	0.005	0.006	0.449	1.193
LN(*DHOS*)	0.042 ***	0.006	0.000	1.411	0.042 ***	0.006	0.000	1.413
LN(*KD*)	0.132 ***	0.019	0.000	3.210	0.130 ***	0.019	0.000	3.221
LN(*DUN*)	0.037 ***	0.006	0.000	1.270	0.037 ***	0.006	0.000	1.271
LN(*DSHS*)	−0.024 *	0.014	0.088	1.014	−0.024 *	0.014	0.081	1.015
SD	0.034 ***	0.009	0.000	1.078	0.034 ***	0.009	0.000	1.079
PR	0.010 ***	0.003	0.001	1.222	0.010 ***	0.003	0.001	1.224
LN(*SIZE*)	0.163 ***	0.016	0.000	1.113	0.161 ***	0.016	0.000	1.116
Intercept	10.903 ***	0.189	0.000		10.551 ***	0.274	0.000	
Adjusted R^2		0.560				0.564		

Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. SE represents standard error of regression coefficient. VIF represents variance inflation factor, which is used to quantify the degree of multicollinearity.

The results of Model (1) indicate that *UR* had a negative effect on housing prices in all districts. The regression coefficient of *UR* is −0.051 at the 1% significance level, indicating that a 1% increase in *UR* is associated with a 0.051% decrease in housing prices. This result indicates that residents were more sensitive to the negative influences of *UR* compared to the convenience of *UR*, which makes them reject the increase in *UR* density.

For the results of Model (2), the regression coefficient of *UR* is similar to that of Model (1). The regression coefficient of the interaction item of *UR* and property management is at the 10% significance level (p-value = 0.092) and the value is 0.020. This indicates that property management has a positive moderating effect on the capitalization effect of *UR* on housing prices. Generally, the negative effect of *UR* on housing prices decreases as the quality of property management increases. For the interaction item of *UR* and building age, the coefficient is −0.003 at the 10% significance level, indicating that the negative effect of *UR* on housing price decreases with improvements in performance of building sound insulation (as the building age decreases). These results are consistent with the fact that property management and performance of building sound insulation (*YEAR*) can reduce the residents' perception that *UR* has a negative influence on environment and society [51,52]. The negative impact of *UR* on residents' quality of life usually decreases residents' preference for *UR*, which leads the demand curve to move to the left and the premium of *UR* to decrease. However, greater property management means better security, which can keep the community isolated from strangers to the maximum extent possible and decrease the potential probability of crime [52]. Furthermore, new buildings usually adopt better construction technologies and construction materials to improve performance of building sound insulation, which effectively insulate residents from adverse environments and create a more comfortable living experience for residents [53]. Therefore, compared with the owners who have housing with bad sound insulation, the demand curve of owners having houses with good sound insulation is further to the right. In other words, they are willing to pay a higher premium for *UR*.

Meanwhile, the coefficient of *PM* is 0.083 at the 1% significance level (the results of Model 1 and Model 2 are approximately the same), which means that property management and building have a direct capitalization effect on housing prices. Further, the coefficient of *YEAR* is −0.014 at the 1% significance level, indicating that newer housing with better performance of building sound insulation are preferred by home-buyers. Therefore, considering the double effect of property management and performance of building sound insulation, developers can achieve higher premiums by adopting better property management services and construction techniques, particularly for houses in areas with high *UR* density. Moreover, there is little difference in the control variables' regression coefficients of Model (1) and Model (2), confirming their robustness.

4.2. Quantile Regression Results

The baseline results of the hedonic price model are reported in Column 1 of Table 3 for comparison. The full quantile regression includes eight estimates from the 20th quantile to the 90th quantile and specifies the capitalization effect of *UR* on different levels of housing prices.

Table 3. Quantile regression results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Global	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
LN(*UR*)	−0.051 ***	0.012 ***	0.006 **	−0.028 ***	−0.045 ***	−0.057 ***	−0.063 ***	−0.079 ***	−0.076 ***	−0.093 ***
	(0.008)	(0.004)	(0.003)	(0.010)	(0.010)	(0.009)	(0.010)	(0.011)	(0.012)	(0.017)
EI	0.080 ***	0.094 ***	0.080 ***	0.079 ***	0.079 ***	0.079 ***	0.074 ***	0.079 ***	0.093 ***	0.071 **
	(0.014)	(0.024)	(0.019)	(0.018)	(0.017)	(0.016)	(0.017)	(0.020)	(0.022)	(0.030)
YEAR	−0.014 ***	−0.007 ***	−0.012 ***	−0.015 ***	−0.015 ***	−0.014 ***	−0.016 ***	−0.015 ***	−0.015 ***	−0.016 ***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
LN(*BUS*)	0.051 ***	0.047 *	0.046 **	0.049 **	0.048 **	0.038 **	0.051 **	0.042 *	0.067 ***	0.055
	(0.016)	(0.028)	(0.022)	(0.021)	(0.020)	(0.019)	(0.020)	(0.023)	(0.025)	(0.035)
LN(*DSUB*)	−0.036 ***	−0.047 ***	−0.038 ***	−0.031 ***	−0.031 ***	−0.035 ***	−0.048 ***	−0.047 ***	−0.046 ***	−0.030 **
	(0.006)	(0.010)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)	(0.009)	(0.013)
LN(*DUC*)	−0.279 ***	−0.243 ***	−0.264 ***	−0.277 ***	−0.284 ***	−0.290 ***	−0.291 ***	−0.286 ***	−0.286 ***	−0.303 ***
	(0.008)	(0.013)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.011)	(0.012)	(0.017)
LN(*DG*)	0.004	0.015	0.019**	0.016**	0.013*	0.007	−0.001	−0.004	−0.013	0.011
	(0.006)	(0.011)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)	(0.010)	(0.013)
LN(*DHOS*)	0.042 ***	0.030 ***	0.041 ***	0.041 ***	0.045 ***	0.048 ***	0.043 ***	0.051 ***	0.045 ***	0.041 ***
	(0.006)	(0.010)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.009)	(0.013)
LN(*KD*)	0.132 ***	0.086 ***	0.105 ***	0.129 ***	0.157 ***	0.168 ***	0.153 ***	0.153 ***	0.133 ***	0.130 ***
	(0.019)	(0.032)	(0.025)	(0.024)	(0.023)	(0.022)	(0.023)	(0.027)	(0.029)	(0.041)

Table 3. *Cont.*

Variable	(1) Global	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
LN(*DUN*)	0.037 *** (0.006)	0.041 *** (0.011)	0.033 *** (0.008)	0.037 *** (0.008)	0.039 *** (0.007)	0.037 *** (0.007)	0.037 *** (0.008)	0.032 *** (0.009)	0.047 *** (0.010)	0.045 *** (0.013)
LN(*DSHS*)	−0.024 * (0.014)	−0.033 (0.023)	−0.014 (0.018)	−0.010 (0.017)	−0.011 (0.016)	−0.009 (0.016)	−0.011 (0.017)	−0.021 (0.019)	−0.025 (0.021)	−0.033 (0.030)
SD	0.034 *** (0.009)	0.030 * (0.016)	0.022 * (0.012)	0.030 *** (0.012)	0.032 *** (0.011)	0.030 *** (0.011)	0.028 ** (0.011)	0.043 *** (0.013)	0.044 *** (0.014)	0.045 ** (0.020)
PR	0.010 *** (0.003)	0.007 (0.005)	0.007* (0.004)	0.008 ** (0.004)	0.007 ** (0.004)	0.010 *** (0.003)	0.010 *** (0.004)	0.010 ** (0.004)	0.009 * (0.005)	0.010 (0.006)
PM	0.085 *** (0.011)	0.089 *** (0.019)	0.072 *** (0.015)	0.063 *** (0.014)	0.078 *** (0.014)	0.086 *** (0.013)	0.086 *** (0.014)	0.077 *** (0.016)	0.095 *** (0.018)	0.086 *** (0.025)
LN(*SIZE*)	0.163 *** (0.016)	0.088 *** (0.026)	0.106 *** (0.021)	0.150 *** (0.020)	0.168 *** (0.019)	0.157 *** (0.018)	0.184 *** (0.019)	0.186 *** (0.022)	0.194 *** (0.024)	0.248 *** (0.033)
_cons	10.903 *** (0.189)	10.780 *** (0.319)	10.734 *** (0.249)	10.613 *** (0.237)	10.540 *** (0.224)	10.699 *** (0.219)	10.940 *** (0.232)	11.031 *** (0.265)	11.082 *** (0.288)	11.026 *** (0.403)
Pseudo R^2	-	0.347	0.357	0.360	0.364	0.368	0.367	0.360	0.351	0.326
Adjusted R^2	0.563	-	-	-	-	-	-	-	-	-
N	2286	2286	2286	2286	2286	2286	2286	2286	2286	2286

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

Table 3 lists the quantile regression results. The pseudo R^2 of all the quantiles is between 0.326 and 0.368, indicating that all models have adequate explanatory power. All the regression coefficients of *LN*(*UR*) are significant at the 1% level, indicating that *UR* has a capitalization effect on all levels of housing prices. However, the capitalization effect on different levels of housing prices is significantly different in heterogenous price quantiles. Specifically, with the increase in housing prices, the coefficients decrease from 0.012 to −0.093. *UR* also shows a positive and negative effect on low-price houses (Q10 and Q20) and medium-/high-price houses (Q30–Q90), respectively. In other words, the owners of low-price houses represent positive demands on *UR*, and the owners of high-price houses resist the increase in *UR* density.

This result be due to various reasons. First, compared to high-price houses, *UR* development is lower in the surroundings of low-price houses. Those living in low-price houses may not be as mobile as the residents of high-price neighborhoods [53]. For example, the owners of high-price houses usually own more private cars and are less sensitive to increases in transportation costs [42]. Therefore, there might be lower demand from the owners of high-price houses for the convenience of *UR* service near their houses. In addition, wealthier residents tend to be more concerned about the privacy and comfort of their homes [20]. More *UR* stores imply increased adverse impacts on the environment, such as noise pollution, large crowds, trash accumulation, and increased crime rate due to the presence of strangers [13]. The owners of high-price houses will show less tolerability to the negative influence of *UR* than those who own low- and medium-price houses. In addition, more job opportunities from high density *UR* areas may also lead to gaps between the demands of the owners of low-price and high-price houses [6]. The above reasons meant that the demand curve of high-price house owners were more to the left than the demand curve of low-price house owners. In other words, high-price house owners are willing to pay a lower premium for *UR*.

4.3. Geographically Weighted Regression Model Results

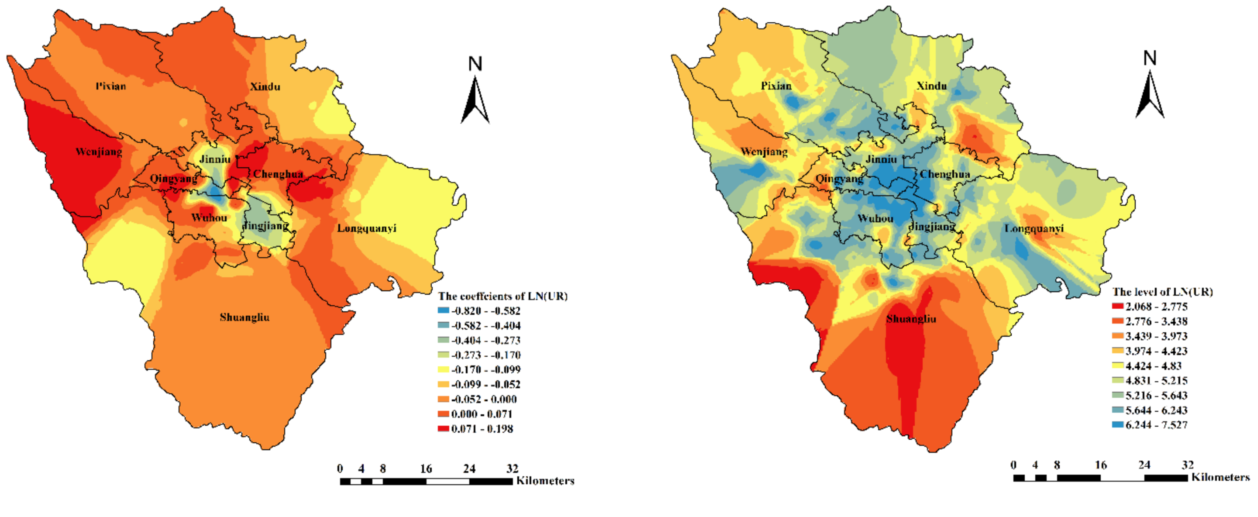
Before building a spatial econometric model of Chengdu housing prices, we test the spatial autocorrelation of the logarithm of housing prices. The Moran I index of logarithm of housing is 0.576 at the 1% significance level (p-values < 0.01), indicating that Chengdu housing prices are characterized by positive spatial autocorrelation and spatial aggregation (the high-price houses are clustered together, as are the low-price houses). Hence, the geographically weighted regression model is used to estimate the spatial heterogeneity of the impact of the above-mentioned explanatory variables on housing prices in Chengdu. Because the regression of coefficients of distance to park or square are not significant in global and all price quantiles, we remove distance to park or square in the geographically weighted regression model.

Table 4 presents the minimum, median, maximum, and mean of geographically weighted regression model results. The adjusted R^2 of the geographically weighted regression model is 0.775, significantly higher than the hedonic price model (0.560), indicating superior explanatory power. Spatial heterogeneity has a significant impact on the capitalization effect of *UR* on housing prices. The regression coefficients of *LN*(*UR*) show both positive and negative values, indicating that residents' demands for *UR* are significantly different in different regions and represents demand and rejection simultaneously.

Table 4. Results of geographically weighted regression model.

Variable	Max	Median	Min	Mean
LN(*UR*)	0.2009	−0.0407	−0.8097	−0.0779
EI	0.2613	0.1276	−0.0526	0.1289
YEAR	0.0098	−0.2566	−0.8356	−0.2699
LN(*BUS*)	0.3468	0.0585	−0.2544	0.0562
LN(*DSUB*)	0.1343	−0.0415	−0.3572	−0.0392
LN(*DUC*)	0.5170	−0.6877	−2.4070	−0.6817
LN(*DHOS*)	0.7616	0.1374	−0.6634	0.1034
LN(*KD*)	0.2712	0.0114	−0.2021	0.0171
LN(*DUN*)	1.5305	0.0077	−1.6244	0.0519
LN(*DSHS*)	0.2499	0.0281	−0.4133	0.0203
SD	0.2027	−0.0037	−0.2645	0.0011
PR	0.4484	0.1332	−0.1476	0.1350
PM	0.2955	0.1254	−0.0812	0.1196
LN(*SIZE*)	1.9464	0.2349	−0.7878	0.2602
Intercept	0.2009	−0.0407	−0.8097	−0.0779
Bandwidth		60		
N		2286		
Adjusted R^2		0.775		

To further examine the influence of spatial heterogeneity, we employ the Kriging method (Figure 3a) to perform spatial interpolation on the coefficients of *LN*(*UR*). Negative coefficients were observed in the core area of Chengdu, with Tianfu Square as the center, while positive coefficients were observed in the peripheral area of Chengdu, particularly in Wenjiang and Pixian districts, which are in the northwest area of Chengdu. In general, the coefficients of *LN*(*UR*) show significant spatial heterogeneity and reflect a nearly circular distribution, which gradually increases outward from the city center (from −0.8097 to 0.2009). In other words, residents in the periphery area need an increased *UR* intensity to realize convenience from *UR*, and residents in the core area reject the increase in *UR* intensity to protect their habitable environment and life equality.



(**a**) (**b**)

Figure 3. Spatial distribution of *LN*(*UR*) and coefficients. (**a**) the spatial distribution of coefficients of logarithm of urban retail; (**b**) represents the spatial distribution of logarithm of urban retail.

Furthermore, we plot the spatial distribution of *LN*(*UR*) (Figure 3b) and assign a reverse color direction (the blue part indicates higher ownership *LN*(*UR*)) for ease of comparison with Figure 3a. We find that the *LN*(*UR*) coefficients have a similar spatial distribution to *LN*(*UR*). Hence, we assume that the regression coefficient of *LN*(*UR*) is related to the level of *LN*(*UR*). This hypothesis is supported by the scatter diagram (Figure 4) between the *LN*(*UR*) and coefficients of *LN*(*UR*). Figure 4 shows that *LN*(*UR*) has a negative impact on the regression coefficients of *LN*(*UR*), which implies that the positive capitalization effect of *LN*(*UR*) on housing prices gradually decreases with the increase in the level of *LN*(*UR*). The fitting straight line indicates that the impact of average *LN*(*UR*) on housing prices shifts from promotion to inhibition when average *LN*(*UR*) reaches 3.441, where the attitude of residents changes from demand to resistance. This shows that there is an inverted U-shaped relationship between *LN*(*UR*) and housing prices. To directly confirm this deduction, we established a new hedonic price model, which introduced the square of *LN*(*UR*). The result is shown in Table A1. From Table A1, we can see that the regression coefficients of the square of *LN*(*UR*) was −0.015 at the 5% significance level, confirming the inverted U-shaped relationship between *LN*(*UR*) and housing prices. Generally, before *LN*(*UR*) reaches the inflection point, *LN*(*UR*) has a positive capitalization effect on housing prices, which decreases with the increase of *LN*(*UR*). After reaching the inflection point, the positive capitalization effect changes to a negative effect on housing prices. This might be due to two reasons: (1) with the increase in *UR*, the demand for the convenience of *UR* eventually plateaus, which leads to a reduction in the willingness to pay for the increase of *UR* convenience and (2) the increase in *UR* will attract more consumers and negatively affect the comfort of the living environment [10,13].

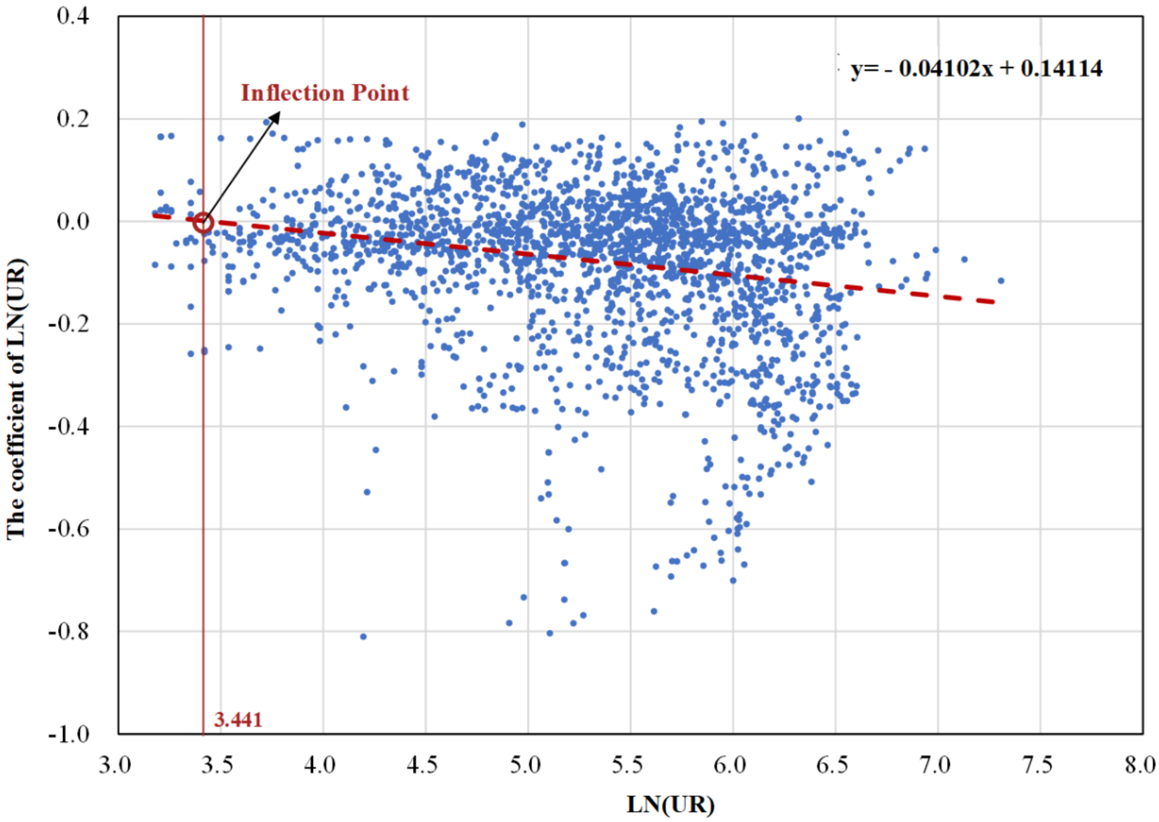


Figure 4. The relationship between *LN*(*UR*) and coefficients.

5. Conclusions

An accurate understanding of the residents' demands for *UR* in heterogeneous conditions is crucial for the *UR* layout of cities. Based on the second-hand housing transaction data of Chengdu, this study employed the hedonic price model, quantile regression, and geographically weighted regression to explore the capitalization effect of urban retail on housing prices and the gap between residents' demands for *UR* in heterogeneous housing characteristics, heterogeneous price quantiles, and heterogeneous space. The main results are as follows: (1) The level of property management (*PM*) and house age (*YEAR*) have a moderating effect on the capitalization effect of *UR* on housing prices. Specifically, good property management and good sound insulation can decrease the negative influence of *UR* on residents' lives; (2) The owners of high-price houses have a lower demand for *UR* compared to the owners of low-price houses; (3) The capitalization effect of *UR* on housing prices is spatially heterogeneous and decreases as we move outward from the Chengdu central area to the Chengdu peripheral area; (4) There is an inverted U-shaped relationship between *UR* and housing prices.

In contrast with previous studies, this study is the first to discuss the inverted U-shaped relationship between housing prices and *UR* and to analyze the moderating effect of housing structure characteristics on residents' demand for *UR*. These research perspectives can provide some reference for further studies on housing prices, such as the relationship between transportation infrastructure and housing prices. For practice, this study also provides several policy implications for real-estate developers and city planning departments. First, considering the negative impact of *UR* on residents' lives, the city planning department should prevent excessive urban retail development in developed areas, which, with a high *UR* intensity or older houses, focuses on regional security and environmental management to offset the negative impacts of *UR*. Specifically, the results of geographically weighted regression indicate that Wenjian and Xindu are more appropriate for *UR* development. On the contrary, Wuhou, Jingjiang and Jinniu should try to decrease their *UR* density. Furthermore, because of the local regression of geographically weighted regression, according to the regression coefficients of houses with similar environments and location variables, planer can find the *UR* development limitation of a specific region. The inverted U-shaped curve indicates that the *UR* intensity of a dwelling district should not be more than 125/km^2 (exp(3.441)/0.5^2). Meanwhile, actively developing the *UR* in boundary areas that have lower *UR* intensity can improve the quality of life of local residents and relieve the pressure on existing commercial areas. Second, real-estate developers should fully focus on consumers' characteristics and adopt different real estate development strategies. Specifically, for consumers with high incomes, real-estate developers should pay more attention to the establishment of a livable and private living environment, since these consumers are not sensitive to the convenience derived from *UR*. On the contrary, the convenience derived from *UR* and reducing the travel cost should be the focus of real-estate developers for consumers with low incomes as the major target consumer group. In addition, by considering the direct and indirect positive impacts of suitable property management and the performance of building sound insulation on housing prices, real-estate developers should consider adopting better property management and sound insulation to increase housing prices, especially in areas with high *UR* intensity.

This study has some limitations. First, it only focuses on the real-estate market in 2019 without considering changes in the capitalization effect of *UR* on housing prices over time. Therefore, residents' demands for *UR* at different times remains unclear. For example, in the past, residents needed to reach retail stores for accessing *UR* activities. Now, residents can enjoy various services without leaving their homes through online shopping platforms such as Meituan and Taobao. Online *UR* reduces the need for physical *UR* resources. Future studies should employ a space–time econometric model and consider variables related to online business. Second, given the strong correlation between different types of *UR*, this study merges all *UR* types. Hence, the impacts of different *UR* types on housing prices and residents' demands for different *UR* types (such as catering, auto service, and clothing sales, among others) are not considered. Finally, because of the limitations of our data, this study does not further discuss the relationship between the residents' demand for urban retail and the employment capacity created by retail, especially for rural areas. These may have some implications for government retail layout plans. Future research should discuss these questions, providing guidance for the optimization of regional internal *UR* structures.

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Appendix A

Table A1. The results of the hedonic price model with $LN(UR)^2$.

Variable	Model (1)				Model (3)			
	Coefficient	SE	*p* Value	VIF	Coefficient	SE	*p* Value	VIF
LN(*UR*)	−0.051 ***	0.009	0.000	1.897	0.107	0.068	0.117	134.689
$LN(UR)^2$					−0.015 **	0.007	0.020	133.717
PM	0.085 ***	0.011	0.000	2.927	0.085 ***	0.011	0.000	2.928
YEAR	−0.014 ***	0.001	0.000	3.745	−0.014 ***	0.001	0.000	3.745
EI	0.080 ***	0.014	0.000	2.108	0.079 ***	0.014	0.000	2.113
LN(*BUS*)	0.051 ***	0.016	0.002	2.491	−0.051 ***	0.016	0.002	2.491
LN(*DSUB*)	−0.036 ***	0.006	0.000	1.227	−0.035 ***	0.006	0.000	1.228
LN(*DUC*)	−0.279 ***	0.008	0.000	1.881	−0.282 ***	0.008	0.000	1.905
LN(*DG*)	0.004	0.006	0.478	1.19	0.004	0.006	0.520	1.191
LN(*DHOS*)	0.042 ***	0.006	0.000	1.411	0.042 ***	0.006	0.000	1.412
LN(*KD*)	0.132 ***	0.019	0.000	3.21	0.127 ***	0.019	0.000	3.247
LN(*DUN*)	0.037 ***	0.006	0.000	1.27	0.037 ***	0.006	0.000	1.27
LN(*DSHS*)	−0.024 *	0.014	0.088	1.014	−0.024 *	0.014	0.085	1.014
SD	0.034 ***	0.009	0.000	1.078	0.034 ***	0.009	0.000	1.079
PR	0.010 ***	0.003	0.001	1.222	0.010 ***	0.003	0.001	1.228
LN(*SIZE*)	0.163 ***	0.016	0.000	1.113	0.163 ***	0.016	0.000	1.113
Intercept	10.903 ***	0.189	0.000		10.551 ***	0.244	0.000	
Adjusted R^2	0.560				0.561			

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

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