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Resource-residential dual drivers: an empirical study on regional heterogeneity in Beijing's secondary housing prices

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Abstract. This research explored the factors that determine housing prices and their regional differences in Beijing's second-hand housing market using complete transaction data from 2024 covering all 16 administrative areas, adopted the Hedonic Price Model and carried out separate Ordinary Least Squares (OLS) regressions for different sub-markets, the results showed a clear two-part difference in how prices were formed which was described as being "resource-driven" compared to "residence-driven", in central urban areas, housing prices were mainly influenced by proximity to top-quality public resources and there was a large price increase for apartments having three or more bedrooms, on the other hand, in suburban zones, market evaluations concentrated more on fundamental living features showing a definite preference for south-facing directions and medium to large sized units, moreover, the additional impacts of important structural elements varied significantly among these regions, the discoveries offered strong empirical proof to back location-specific regulatory measures for the existing housing supply in mega-cities such as Beijing and also provided useful information for market players including house buyers, builders and policymakers enabling them to make better-informed decisions in line with the main value influences in each market section.

Keywords: Beijing second-hand housing, regional heterogeneity, feature price model

1. Introduction

In China's first-tier cities, the existing housing stock now dominates the market, and the secondary housing sector exhibits increasing diversity. As a capital-abundant metropolis, Beijing witnessed second-hand housing transactions comprising over 75% of total housing deals in 2024. Properties in key districts such as Dongcheng and Xicheng demonstrate strong price resilience. In contrast, suburban housing serves primarily residential purposes, leading to pronounced structural market differentiation. Although prior research has confirmed the influence of housing characteristics on prices, most studies rely on pre-2020 data.

This study addresses two core questions: whether large-scale regional differences exist in Beijing's second-hand housing price formation, and whether such differences follow a dual pattern characterized by "core-district-driven" versus "suburban-area-driven" forces, providing practical insights for market participants and policymakers.

Regarding importance, from a theoretical perspective, this paper takes Beijing as an example for study to measure the impacts of housing features on prices and disclose regional differences via a feature-price model.

Novel contributions are shown in three respects. First of all, it utilized comprehensive 2024 city-wide data which reflected the most recent market features after the deepened regulation. Secondly, it conducted precise coding for attributes like unit type and location to reduce information loss to the greatest extent. Thirdly, it incorporated differences in resource endowments to explain the different price mechanism logics, namely the "dynamics driven by resources in central districts compared with those driven by residential demand in suburban areas", thus strengthening the explanatory capacity of the heterogeneity analysis.

2. Literature review

The hedonic price model is regarded as the central theoretical framework for housing price research and Lancaster put forward the theory of consuming heterogeneous goods [1], whereas Rosen improved its econometric analysis system; at the heart of its logic was the notion that housing prices could be broken down into the total of implicit prices for single attributes which laid a strong basis for quantifying the connection between property traits and prices [2]. Domestic scholars had widely utilized this model in research on first-tier cities. Shen et al. by using Beijing's second-hand housing data, verified the great impact of elements like location, the age of the property and transportation convenience and among them, location turned out to be the main positive factor which provided important understandings regarding Beijing's housing price formation mechanisms [3].

Concerning the aspects of influencing elements, at the macro-scale, Chen et al. pointed out that population migration and anticipations impacted housing prices via supply-demand regulation and as a super-large city, Beijing's traits of population concentration and resource gathering further enhanced the propagation impacts of these macro-level elements [4]; micro-level research laid more emphasis on the particular characteristics of the housing itself and its surrounding areas and existing studies mainly centered around property traits, location aspects, and neighborhood qualities, Shen et al. discovered that the quantity of bedrooms in Beijing's second-hand houses had a positive impact on prices while the building's age had a negative one [3] and Ji et al. supported this in their study of other cities, verifying the common driving function of central area attributes and transportation infrastructure in property prices [5]; it was worth noting that the influences of these elements on property prices were not the same everywhere and the regional difference in real estate prices had long been acknowledged in academia whose main point was that the strength and direction of influencing elements varied depending on spatial position and this phenomenon resulted from different transmission mechanisms brought about by urban functional division, differences in resource endowments, and policy interventions [6].

When it came to Beijing's secondary housing market specifically, previous research had shown that there was an imbalance between supply and demand as well as substantial differences in prices between the central and outer-lying regions, but there were still obvious gaps in the research as the timeliness of the data was insufficient because most of the studies depended on data before 2020 which couldn't show the recent market tendencies and the regional differences hadn't been broken down enough since there wasn't much quantitative study on how housing preferences and building features affected things between the downtown districts and the suburbs [7].

In general, although previous research has demonstrated that there is regional disparity in Beijing's secondary housing prices and has also determined its main influencing elements, most of these studies rely on historical data before 2020 which finds it difficult to mirror the most recent market traits after more stringent regulation was implemented, and at the same time, quantitative contrasts between central areas and outlying regions regarding things like layout preferences and the influence of building features still remain rather restricted without detailed empirical proof about the mechanism of "resource-residential" two-factor differentiation, so this paper centered on the most recent one-year data from 2024, simplified variable configurations while stressing regional disparity analysis aiming to deal with the shortcomings in earlier studies where there wasn't enough comparison between outlying and central area mechanisms.

3. Data and research methodology

3.1. Data sources and processing

3.1.1. Data sources

The research data came from the Beike real estate website. The 2024 Beijing second-hand property transaction data included 12 variables. There were 85,124 valid samples.

3.1.2. Variable definition and processing

Table 1. Variable definitions and explanations

Variable Name	Variable Type	Variable Definition and Assignment Notes
price	Dependent Variable	Transaction price per square metre for second-hand properties, measured in yuan per square metre
ln_price	Dependent variable (core)	Natural logarithm of price, employed to mitigate the right skewness in the transaction price distribution; serves as the core dependent variable for subsequent empirical analysis
area	Core explanatory variable (property characteristics)	Property area, measured in square metres, characterising the physical spatial scale of the dwelling
house_type_1	Core explanatory variable (property characteristics)	Virtual variable for dwelling layout: Assigned value 1 for one-bedroom layouts; reference group is two-bedroom layouts
house_type_3	Core explanatory variable (housing characteristics)	House type dummy variable: Assigns value 1 to 3-bedroom and larger units; 2-bedroom units serve as the reference group
orientation	Core explanatory variable (property characteristic)	South-facing unit dummy variable: Assigned value 1 when the property has a south-facing orientation (including purely south-facing, north-south facing, etc.)
floor		Mid-to-High Floor Dummy Variable: Assigns a value of 1 when the property's floor level is at or above the 50th percentile of the total number of floors.
core	Core explanatory variable (location characteristic)	Core District Dummy Variable: Assigns a value of 1 when the property is located in Dongcheng District, Xicheng District, Haidian District, or Chaoyang District; assigns a value of 0 for all other administrative districts
month	Control variable	Peak Transaction Season Dummy Variable: Assigns a value of 1 when the transaction occurred between March and May
Cycle		Transaction cycle, measured in days, depicting the time taken from listing to completion of a property transaction

This study took Beijing's 2024 second-hand property transaction data as its research sample, the raw data included listing and transaction information covering all 16 administrative districts. After initial screening, 81,012 valid samples were kept. The operational definition of "key areas" was based on Beijing's spatial layout criteria for main functional zones.

Concerning variable definitions (Table 1), the dependent variable was the transaction price per square meter of second-hand housing measured in yuan per square meter. Key explanatory variables covered both housing features and location properties, and the orientation and the floor was a dummy variable. The location aspect was employed to measure central attributes; control variables included the peak transaction season and the transaction cycle.

3.2. Research methodology

3.2.1. Benchmark model: OLS linear regression

This study employs an OLS linear regression model to identify the marginal impact of housing characteristics on second-hand property prices. The model specification is as Equation (1):

$$ln\_price = \beta_0 + \beta_1 area + \beta_2 house\_type_1 + \beta_3 house\_type_3 + \beta_4 orientation + \beta_5 floor + \beta_6 core + \beta_7 month + \beta_8 cycle + \mu \tag{1}$$

Where β_0 denotes the constant term, β_i (where i = 1, 2, ..., 8) represents the coefficients of respective variables, and μ signifies the random error term. All variables underwent standardization to eliminate dimensional differences that could distort coefficient comparisons. A positive coefficient implies that the characteristic raises house prices, on the other hand, a negative one shows a reduction, and the magnitude of the coefficient demonstrates the intensity of the impact.

3.2.2. Extended analysis: regional heterogeneity regression

To explore if there were regional distinctions in the price impacts of housing traits, this research split the sample into two categories according to the spatial concentration of Beijing's top-tier public assets (education, healthcare, and commerce), namely the "Central Zone" and the "Suburban Zone", and then carried out OLS regression separately for the base model in each group, and by contrasting the differences in the signs, significance, and sizes of coefficient values for each characteristic variable between the two sets of outcomes, it disclosed the disparities in the housing price influence process under diverse resource endowments.

3.2.3. Robustness tests

To verify the dependability of the benchmark outcomes, this research utilized a sturdiness test through substituting the dependent variable, that is to say, it replaced the initial dependent variable "logarithm of transaction price per unit" with "logarithm of total transaction price" and then re-estimated the OLS model; had the sign of coefficients, statistical significance, and relative influence of key explanatory variables stayed the same as those in the benchmark findings after replacement, it would have shown that the central conclusions of the study were robust.

4. Empirical results analysis

4.1. Descriptive statistics

Table 2 presents the descriptive statistics for all variables in this research which encompassed 81,012 second-hand property transaction records in Beijing and the variables were classified into continuous ones and dummy variables in order to clearly exhibit their distribution features.

4.1.1. Distribution characteristics of continuous variables

For continuous variables, the average transaction price per square meter (price) reached 52,760.054 yuan and had a standard deviation of 25,175.1, its values ranged between 10,006 and 149,956 which showed great dispersion; the average property area (unit: square meters) was 84.543 and there was a standard deviation of 38.088, this meant that most properties in the sample were small to medium-sized units and was the same as the main layout structure of Beijing's existing housing stock; the average transaction period (unit: days) was 101.962 and had a standard deviation of 112.599.

4.1.2. Distribution characteristics of dummy variables

The average for one-bedroom units was 0.196, three-bedroom-and-above units had an average of 0.269, with the rest of the samples relating to the reference group (two-bedroom units). The average value for south-facing orientation was 0.819. This matched the preference in northern cities' housing markets for south-facing sunlight exposure. The average core area value was 0.509, and this fairly even distribution between core and non-core areas significantly reduced regional sample bias that might have interfered with later estimations. The descriptive statistics (Table 2) were shown below.

Table 2. Descriptive statistics

Variable Name	Sample Size	Maximum	Minimum	Mean	Standard deviation	Median	Variance	Kernel	Skewness	Coefficient of Variation (CV)
price	81,012	149,956	10,006	52,760.054	25,175.1	46,856.5	63,378,565.983	0.678	0.964	0.477
area	81,012	567.8	8.1	84.543	38.088	77.25	1,450.659	13.822	2.578	0.451
house_type_1	81,012	1	0	0.196	0.397	0	0.157	0.356	1.535	2.028
house_type_3	81,012	1	0	0.269	0.444	0	0.197	-0.917	1.041	1.648
orientation	81,012	1	0	0.819	0.385	1	0.148	0.743	-1.656	0.47
floor	81,012	1	0	0.707	0.455	1	0.207	-1.168	-0.912	0.643
core	81,012	1	0	0.509	0.5	1	0.25	-1.999	-0.037	0.981
month	8,1012	1	0	0.245	0.43	0	0.185	-0.589	1.188	1.757
cycle	81,012	1,743	1	101.962	112.599	67	12,678.581	12.137	2.638	1.104

4.2. Benchmark regression results

This study built a benchmark econometric framework founded on the characteristic price model and utilized Ordinary Least Squares (OLS) for estimating the impact mechanism regarding Beijing's second-hand property prices; the relevant regression outcomes were presented in Table 3 and the analysis sample included 81,012 valid transaction records.

Table 3. Benchmark regression results

Linear regression analysis results n = 81,012									
	Unstandardised Coefficients		Standardised Coefficients	t	*p*	VIF	R^2	Adjusted R^2	F
	B	Standard Error	Beta						
Constant	10.465	0.006	-	1,843.209	0.000***	-			
area	0	0	-0.038	-10.903	0.000***	1.686			
house_type_1	-0.046	0.004	-0.038	-12.572	0.000***	1.262			
house_type_3	0.08	0.004	0.074	22.352	0.000***	1.529			
orientation	0.018	0.003	0.014	5.194	0.000***	1.089	0.42	0.42	F = 7,336.995 p = 0.000***
floor	-0.009	0.003	-0.009	-3.241	0.001***	1.003			
core	0.619	0.003	0.644	238.478	0.000***	1.019			
month	0.035	0.003	0.031	11.579	0.000***	1.001			
cycle	0	0	-0.019	-6.986	0.000***	1.01			
Dependent variable: ln_price									

Note: ***, **, * denote significance levels of 1%, 5%, and 10% respectively

Model fit goodness-of-fit R^2 = 0.42 indicates that the selected explanatory variables account for 42% of the variance in the logarithm of second-hand property prices. The adjusted coefficient R^2 is consistent with the original coefficient R^2. The F-test statistic was 7,336.995 (p < 0.001). The Variance Inflation Factor (VIF) for all explanatory variables was above (Table 3).

Regarding the estimated results for the core explanatory variable: the unstandardised coefficient for the core area variable 'core' is 0.619 (p < 0.001), with a standardized Beta coefficient reaching 0.644, making it the most influential factor among all variables; its economic implication being that the logarithm of property prices in core areas is 0.619 times higher than the non-core average, corresponding to an actual price premium of approximately 85.7% ($e^{0.619} - 1$). This signifies that core location attributes constitute the primary driver of Beijing's second-hand property prices, aligning with the market characteristic of resource concentration in central districts. The housing type variable exhibits significant structural differences: 3-bedroom and above has a coefficient of 0.08 (p < 0.001), corresponding to an actual premium of approximately 8.3% ($e^{0.08} - 1$). This indicates that such units command higher prices than the 2-bedroom benchmark group, reflecting market preference for larger, upgraded properties; one-bedroom units yielded a coefficient of -0.046 (p < 0.001), corresponding to an actual discount of approximately 4.5% ($1 - e^{-0.046}$), indicating the price disadvantage of smaller units relative to the two-bedroom benchmark group. Among building characteristic variables, south-facing units produced a coefficient of 0.018 (p < 0.001), corresponding to an actual premium of approximately 1.8%, indicating a modest price premium for south-facing units due to superior natural light. The coefficient for mid-to-high floors was -0.009 (p = 0.001), corresponding to an actual discount of approximately 0.9%. This marginal negative effect may stem from the relative scarcity of low-floor properties in core areas (e.g., older estates with premium school catchment zones). Regarding control variables, the coefficient for month (peak transaction season) was 0.035 ($p < 0.001$), corresponding to an actual premium of approximately 3.6%. This indicates that properties transacted between March and May command slightly higher prices than other months, reflecting the modest impact of seasonal market fluctuations. The economic effects of area and transaction cycle are negligible.

4.3. Sub-regional regression results (core districts vs. suburbs)

To further examine the structural distinctions within Beijing's secondary housing market, the sample was divided into two regional groups: the central areas and the suburban outskirts. Separate OLS regressions were estimated for each group (Table 4). This regional division is grounded in the differing resource endowments across Beijing. Central districts concentrate top-tier public resources such as education, healthcare, and commercial facilities, with housing value largely derived from this scarcity. In contrast, suburban areas exhibit a more even distribution of resources, causing housing value to depend more on the inherent comfort and physical attributes of the properties themselves. This disparity in resource allocation directly contributes to heterogeneity in the factors influencing property prices across regions.

Table 4. Comparison of regional regression results

Variable Name	Core Area Coefficient (*p*-value)	Suburban Coefficient (*p*-value)	Interpretation of Differences
area	-0.001 (0.000***)	0 (0.001***)	Core regions have a slightly negative effect on property prices while suburban areas have a positive one which shows that central areas are short of small-unit options and lack strong large-unit premiums.
house_type_1	-0.034 (0.000***)	-0.057 (0.000***)	The discount rate for suburban one-bedroom units (5.7%) exceeds that of the core area (3.4%), indicating a greater preference for larger units in suburban areas
house_type_3	0.139 (0.000***)	0.019 (0.000***)	The premium for larger units in the core area (13.9%) is significantly higher than in the suburbs (1.9%), indicating stronger demand for upgraded housing in the core area
orientation	0.001 (0.838)	0.04 (0.000***)	South-facing units within the central part don't command an obviously higher price while those in the suburbs do, showing a remarkable difference of 4% because the facilities in the center are not as good which lessens the effect that the direction has.
floor	-0.009 (0.029**)	-0.007 (0.106)	Mid-to-high floors in core areas show a marginally negative significance, while suburban areas show no significance. Lower floors in core areas (such as older, smaller, and less desirable school district properties) are even scarcer.
month	0.022 (0.000***)	0.047 (0.000***)	Suburban peak-season premiums (4.7%) exceed those in the core area (2.2%), indicating greater seasonal influence on suburban markets
cycle	0 (0.013**)	0 (0.000***)	The negative impact of transaction cycles on property prices is more pronounced in suburban areas, where market liquidity exhibits greater sensitivity to price fluctuations

Note: *** and ** denote significance levels of 1% and 5% respectively; coefficients are unstandardised, with premium rates approximated via exp(coefficient)-1.

The regional differentiation of key explanatory variables is evident. The baseline regression confirms the strong premium effect of core area location. Further sub-regional analysis reveals that housing value in core districts is driven primarily by "resource occupancy". For instance, the coefficient for three-bedroom and larger units reaches 0.139 ($p < 0.001$), implying an actual price premium of about 13.9%, substantially higher than the 1.9% observed in suburban zones. Conversely, one-bedroom units receive a larger price discount in the suburbs (5.7%) compared to core areas (3.4%). This indicates suburban buyers' preference for functionally complete medium-to-large units, while small units in core areas maintain a relatively smaller discount.

Differences in physical characteristics align with regional valuation logics. In core zones, the south-facing orientation coefficient is only 0.001 and statistically insignificant, whereas in suburban regions it reaches 0.04 ($p < 0.001$), equivalent to a 4% premium. For middle-to-high floors, a slight but significant negative effect exists in core areas (coefficient – 0.009, $p = 0.029$), while it is insignificant in suburbs.

Variations in control variables further reinforce market segmentation. The peak-season transaction premium (4.7%) in suburban areas far exceeds that in core districts (2.2%). The negative effect of transaction cycle length is more pronounced in suburban areas, indicating lower market liquidity compared to central districts. Longer listing times in suburbs increase buyer bargaining power, whereas limited housing availability in core areas sustains strong demand support, mitigating the price impact of transaction duration.

The influence of property area also exhibits divergent regional tendencies. The coefficient in core districts is –0.001 ($p < 0.001$), while in outlying areas it is 0 ($p < 0.001$). In core areas, the marginal benefit of added resources diminishes as size increases, resulting in a slightly negative area-price relationship. In suburban areas, where owner-occupancy dominates, greater floor space directly enhances living comfort. However, this effect is attenuated by factors such as layout configuration.

Overall, the regional regression results demonstrate that differences within Beijing's second-hand housing market stem mainly from two distinct value systems: one "resource-centered" and the other "residence-focused". In core areas, housing serves primarily to access scarce resources such as high-quality schools and prime locations, which exert a stronger influence on prices than physical attributes. In suburban areas, housing functions more as a living product, with prices depending largely on comfort-related features such as orientation and unit size, while resource-based advantages play a minor role.

4.4. Robustness tests

To verify the sturdiness of the benchmark regression outcomes, this research substituted the dependent variable with the natural logarithm of second-hand property transaction prices (ln_total_price) and reran the OLS regression (Table 5). The findings showed that the central explanatory variables retained the same coefficient directions as in the benchmark regression and stayed statistically significant at the 1% level, and it was noteworthy that the coefficient for core location was 0.592 ($p < 0.001$), and that for south-facing orientation was 0.023 ($p < 0.001$), which verified the firmness of the main findings about how housing and location features influence property prices, while only the coefficient for the mid-to-high floor turned out to be insignificant after the replacement of the dependent variable ($p = 0.352$).

This research carried out an additional separate regression where the logarithm of transaction price served as the dependent variable and floor was the only independent variable (Table 6). It was found that the coefficient for floor was -0.005 ($p = 0.212$) which did not reach the significance level.

Table 5. OLS regression results for second-hand property transaction prices

Linear regression analysis results n = 81,012									
	Non-standardised coefficient		Standardisation coefficient	t	p	VIF	R^2	Adjusted R^2	F
	B	Standard Error	Beta						
Constant	4.914	0.006	-	840.005	0.000***	-			
area	0.008	0	0.517	179.754	0.000***	1.686			
house_type_1	-0.212	0.004	-0.141	-56.618	0.000***	1.262			
house_type_3	0.115	0.004	0.085	31.036	0.000***	1.529			
orientation	0.023	0.004	0.015	6.359	0.000***	1.089	0.603	0.603	F = 15,358.807 p = 0.000***
floor	0.003	0.003	0.002	0.93	0.352	1.003			
core	0.592	0.003	0.495	221.312	0.000***	1.019			
month	0.033	0.003	0.024	10.68	0.000***	1.001			
cycle	0	0	-0.02	-8.851	0.000***	1.01			
Dependent variable: ln_total_price									

Note: ***, **, * denote significance levels of 1%, 5%, and 10% respectively

Table 6. Results of the floor variable in a standalone regression

Linear regression analysis results n = 81,012									
	Unstandardised Coefficients		Standardised Coefficient	t	p	VIF	R^2	Adjusted R^2	F
	B	Standard Error	Beta						
Constant	10.765	0.003	-	3,447.667	0.000***	-	0	0	F = 1.561 p = 0.212
floor	-0.005	0.004	-0.004	-1.249	0.212	1			
Dependent variable: ln_price									

Note: ***, **, and * denote significance levels of 1%, 5%, and 10% respectively

5. Conclusion

This paper analyzed how housing characteristics influenced second-hand property prices and regional differences among Beijing's 16 administrative districts in 2024 by using a characteristic price model and region-specific regression techniques.

The central idea shows a clear "two-track difference" in the mechanism by which Beijing's second-hand housing prices are formed, which originally comes from the differences in regional resource endowments and leads to different value patterns driven by "resource-related" and "residential-related" elements; in the basic regression analyses, the location in the central area (core), the type of housing (house_type_3), and the time of transaction (month) became important factors determining the price, and the influence of the central area properties was the most significant, which verified that the valuable public resources play a crucial part in price determination, while the physical features of the houses (such as direction, size) had relatively moderate effects on the price and were influenced by regional characteristics.

Regional differentiation shows up in two different ways: First, as "carriers of resources", the housing prices in the core areas are mainly influenced by scarce public resources such as top-level education and medical care; three-bedroom or bigger apartments have a 13.9% higher price, which is much more than the 1.9% in the suburbs, and features that make living more comfortable, like facing south and being on mid-to-high floors, are less important compared to the scarcity of these resources so they don't affect the price much, second, in the suburbs, houses work as a "product for living", and the price depends on how good it is for living, southern-facing units cost 4% more, while one-bedroom units get a bigger discount (5.7%) than those in the core areas (3.4%), showing that suburban buyers put more importance on living comfort and practicality.

Multidimensional confirmation further strengthens the central findings: the property area has a slightly negative impact in the central part and a moderately positive one in the outskirts, which verifies the market difference between the central area's "allocation of low-total-price resources" and the outskirts' "predominance of owner-occupier demand", and regional differences in transaction periods and peak months show that there is more stable demand in central neighborhoods when contrasted with the outskirts, which is highly consistent with Beijing's secondary housing market situation where "there is rigid demand in central regions as opposed to flexible demand in outer areas".

References

[1] Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy, 74*(2), 132–157.

[2] Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy, 82*(1), 34–55.

[3] Shen, T. Y., Yu, H. C., Zhou, L., Gu, H. Y., & He, H. H. (2020). Mechanisms influencing second-hand residential property prices in Beijing: A study based on the multi-scale geographically weighted regression (MGWR) model. *Economic Geography, 40*(3), 75–83. https: //doi.org/10.15957/j.cnki.jjdl.2020.03.009

[4] Chen, X. L., Chen, K., Wang, Z. R., & Xiao, Z. Y. (2024). Factors influencing inter-city housing price differentiation. *Economic Theory and Management, 44*(2), 49–64.

[5] Ji, Y. F., Dai, L., Ding, Z. J., Dong, Y. C., & Li, S. W. (2022). Influencing factors and spatial effects of secondary housing prices in cities: An empirical study of Nanjing based on the MGWR model. *Resource Development and Market, 38*(7), 777–783, 896.

[6] Qiang, H. H., Wang, H., & Lei, S. Y. (2024). Spatial differentiation characteristics and influencing factors of housing prices in large cities based on the MGWR model: A case study of Nanjing's main urban area. *Modern Urban Research*, (4), 109–116.

[7] Li, J. J., Sun, C. S., Zhang, C. Y., & Hu, X. Q. (2024). Spatial heterogeneity of factors influencing urban residential property prices based on a multi-scale geographically weighted regression model: A case study of Guilin's main urban area. *Journal of Zhejiang University (Science Edition), 51*(5), 623–635.