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An Investigation of Site Selection Decisions of Residential Development Projects in Hangzhou Based on Potential Market Segmentation

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Abstract: Since 2016, strict regulatory policies have limited the size and financing channels of China's urban real estate market. To adapt to the new situation, real estate developers need to adjust their development strategies and adopt more precise investment methods. In this respect, cost reduction, an accurate market positioning, and conducting detailed market research are particularly crucial. Given that the uneven development of the urban housing market has exacerbated urban segregation, urban residential space was subdivided into multiple potential submarkets. This study focuses on the land acquisition and the development of commercial residential projects in Hangzhou, China, from 2003 to 2022. Using the latent class analysis method based on the discrete choice model, the potential submarkets of Hangzhou's housing development market are identified, and the project positioning and land selection preferences of developers are assessed. The results show that Hangzhou's residential projects can be divided into five potential market categories: high-rise basic demand dwellings, high-end-improvement-type dwellings, luxury low-density dwellings, primary-improvement-type dwellings, and large-scale mixed-density dwellings. The importance of different land elements for developers when developing various types of projects is evaluated by calculating the willingness-to-pay coefficient. The findings of this study provide a comprehensive perspective for the government, real estate developers, and property owners to better understand the development dynamics on the supply side of the real estate market.

Keywords: real estate market; residential developers; latent class analysis; project positioning; project site selection

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1. Introduction

Since the commercialization of China's housing market, the real estate market has boomed. According to the China Statistical Yearbook, the proportion of the real estate market in China's gross domestic product (GDP) has increased from 4.10% in 2000 to 7.20% in 2020. However, the booming real estate market has also generated several social problems and unhealthy development patterns, including inadequate financial systems, insufficient supervision, and lack of market awareness [1]. Developers have long adopted a development model characterized by high turnover and high debt, relying on continuous cash flow, and that is fraught with hidden dangers. At the end of 2016, the Central Economic Work Conference first proposed that "houses are for living, not for speculation". On 20

August 2020, relevant departments proposed "three red lines" to restrict the financing of real estate enterprises. The tightening of policies sounded the alarm for the development of the real estate industry, and developers need to re-examine how reasonable their development strategies are.

At the micro-level of urban development, developers usually adopt different development methods for land parcels in different locations of the city, according to their own interests and the needs of urban functional zoning. At present, clear functional zoning is included in the spatial development of cities both in China and internationally. Currently, the development of the majority of cities in China usually presents a concentric structure, articulated into a core circle, a growth circle, and an outer circle [2]. The development methods of developers will also entail similar differences in different circles of the city, which is divided into distinctive "residential development submarkets". In addition, the real estate market and the land market interact reciprocally, and changes in real estate developers' estimates of housing prices will significantly alter their strategies in the land market [3]. In a market environment such as the current housing market in China, marked by heightened competition and stringent policies, to secure their profitability, residential developers must adopt more precise market positioning strategies and ensure rational land acquisition and investment practices in the development stages [4].

Hangzhou is an economically developed city located on the eastern coast of China, and the prosperity of its real estate market has always been at the national forefront. According to data from the National Bureau of Statistics of China, the investment scale and the average housing prices in Hangzhou's residential market have been steadily increasing since 2015. In this respect, in 2022, the city ranked at the top among China's large and medium-sized cities, with housing prices second only to the three first-tier cities of Beijing, Shanghai, and Shenzhen. In addition, differences exist in housing prices among different locations within Hangzhou. Residential prices in the central area of the city are considerably higher than those in the peripheral areas, and the closer an area is to the center of the main urban area, the higher the concentration of development. West Lake is a famous scenic spot, located in the central urban area of Hangzhou. The scarcity of landscape resources makes the new residential areas surrounding this spot high-end and expensive. At the same time, to protect the open view of the lake, the surrounding buildings have certain height requirements, and the construction of high-rise buildings is restricted. In some beautiful areas near the city, such as Xixi Wetland Park, the residential land is usually characterized by low-density-landscape luxury homes or large residential areas. As such, the city seems to have formed "submarkets" with different market positioning, with developers also adopting different residential development methods across different areas. Are there submarkets of different product types in the Hangzhou residential market? Will developers consider the matching of location and product type in their land selection decisions, or will they choose suitable land locations based on their own product development characteristics? To date, these questions have not been properly addressed. This study explored residential project types by associating parcels and project information, using the latent class analysis (LCA) method, and investigated the site selection characteristics of different types of projects, as well as the payment willingness of developers for different location characteristics. Through an empirical investigation of the housing market in Hangzhou, this study aimed to analyze the determinants and the behavioral logic of land selection and product positioning of developers, so as to improve the understanding of the behavioral pattern of the supply side of the housing market and the psychological activity of the demand side of the land market, and to provide a basis to promote the coordinated development of the land market and the housing market. It will also be beneficial for government management departments to further improve urban planning and enhance the level of public facility supply. Although cities are characterized by different housing prices and housing quality levels, large and medium-sized Chinese cities have similar policy background and market characteristics. Developers may have different product positioning in different cities; however, their behavior logic from land acquisition to development is consistent. Although this study performed an empirical investigation based on Hangzhou data, the results have a certain reference value to understand and improve the real estate market supply in other cities. As for foreign real estate markets, characterized by different systems, this study provides a basis to understand the commonalities in developers' behaviors and the similarities and differences of specific concerns across different contexts.

This paper is structured as follows: Section 2 presents a review of the existing literature. Section 3 explains the data sources and the corresponding model methodology. Section 4 discusses the potential submarkets and their land selection in Hangzhou. Section 5 presents the discussion and implications of this study. Finally, Section 6 describes the conclusions of this study.

2. Literature Review

2.1. The Basic Theory of Residential Submarket Formation

The real estate market is often divided into submarkets, each characterized by distinct spatial and non-spatial attributes [5,6]. Submarkets are defined as groups of dwellings that exhibit high internal homogeneity while maintaining significant external heterogeneity [7]. This concept is grounded in the principle of substitutability, whereby housing prices within a certain submarket are similar because the submarket consists of close substitutes [8]. Waddell et al. [9] suggested that residents aim to maximize the value of their living space, leading to distinct residential patterns. Hu et al. [10] argued that the heterogeneity of urban spaces is inevitable as cities develop. People with similar backgrounds and lifestyles often settle in areas that meet their specific needs, reinforcing social identity and belonging. Factors such as income level, public services (e.g., schools, parks, and medical facilities), housing prices, and accessibility to transportation influence these choices, resulting in the segregation of urban spaces [11–14]. This segregation leads to clusters of similar social groups, creating submarkets with varying characteristics.

Additionally, employment opportunities, housing costs, and construction year also play an important role in residential location decisions [15]. Zhang and Kockelman [16] and Cox and Hurtubia [17] found that housing price demand converges in similar socio-economic groups, reinforcing the formation of residential submarkets. Moreover, Feng and Han [18] noted that housing price differences also contribute to regional development imbalances, as land availability and residents' preferences generate residential segregation and diversity in urban spaces.

2.2. Decision Factors for Supply-Side Site Selection and Project Development

The site selection and project development decisions of developers are shaped by various factors, including geography, land price, and the anticipated return on investment. In particular, location remains one of the most critical determinants of project success. Developers tend to build low-density housing in suburban and scenic areas, while high-density projects are more common near city centers, contributing to the economic development of urban cores [19,20]. While developers are often reluctant to invest in remote areas due to perceived risks [2], proximity to infrastructure such as transportation hubs, subways, and public services is highly valued for its positive impact on property prices [21–23].

Land price is another critical concern. Developers typically favor lower-priced land to capitalize on potential price appreciation in a fluctuating market [24–26]. However, larger-scale developers with previous bidding success may bid higher, reflecting their greater ability to absorb costs [27,28]. Recently, scholarly attention has shifted to housing layout and unit design. Wei [29] used Maslow's hierarchy of needs to classify young Chinese homebuyers into four demand categories: rental, first-time purchase, upgraded housing, and multiple property investment. Developers must cater to these diverse needs, offering a range of unit sizes and configurations. In high-density cities, the optimization of layouts in high-rise buildings can improve living quality and sales potential [30].

In the current context of downturn in China's real estate market, developers should give more consideration to the experience of residents. More in detail, they should pay further attention to a better and more civilized living quality for modern residents, as this will be more conducive to the accumulation of developers' reputation and the increase in their sales revenue.

2.3. Research on Submarket Segmentation and Location Selection

Various methods have been employed in the literature to identify residential submarkets, the most common being the hedonic price model and cluster analysis. However, these traditional methods have limitations. The hedonic price model often verifies submarkets' existence rather than discovering them, while cluster analysis can require substantial subjective input and data [17,31,32]. To address these limitations, recent research has shifted toward using endogenous segmentation techniques, such as the latent class model (LCM), which relies on latent variables to explain the interactions between observable indicators and categories [33]. The LCM is particularly useful to identify submarkets and understand developers' land selection preferences, reducing the biases of traditional methods [34–37].

The majority of existing studies on submarket segmentation focus on the demand side, analyzing buyer behavior based on factors such as income, age, family size, and commuting time [15,38]. Fewer studies focus on the supply side, specifically on developers' land selection and project development behaviors. This study contributes to the existing literature by examining how developers segment residential submarkets based on project characteristics, such as unit layout and location, and assessing how they make land acquisition decisions. Given China's current real estate environment, characterized by a shift away from speculative investments toward meeting basic housing needs, this study offers timely insights into how developers can adapt their strategies in similar market contexts.

By adopting this perspective, this study provides valuable guidance for developers and policymakers in the real estate sector, particularly in balancing market demands with the provision of affordable, high-quality housing.

3. Empirical Research Design and Data

3.1. Data Acquisition and Variable Construction

In this study, data were collected for the main urban area of Hangzhou, covering eight administrative districts: Shangcheng, Gongshu, Xihu, Binjiang, Xiaoshan, Yuhang, Linping, and Qiantang. Information was gathered on 1061 residential projects that acquired land from 2003 to 2022 and were launched between 2004 and 2023. The detailed characteristic variables of these residential projects were primarily sourced from the database of the China Real Estate Information Corporation (CRIC), which is China's largest real estate information and consulting service provider.

First, residential projects in Hangzhou were classified using their characteristic variables (X_n). For this purpose, referring to previous research and considering data availability, this study mainly employed the following categories of variables: property characteristics, project scale, price, and unit type. Property characteristics include greenery rate, floor area ratio, number of buildings, parking ratio, and project land area. The average transaction price of the residences was calculated based on the unit price information recorded in the CRIC database. To accurately classify the grade of residences, this study introduced the variable "unit type ratio." According to the standards for the payment of deed tax[1] in major cities in China, this study divided the residential units into four types (where x represents the unit area): basic demand units ($x \leq 90$ square meters), medium units ($90 < x \leq 144$ square meters), large units ($144 < x \leq 200$ square meters), and luxury units ($x > 200$ square meters). Then, the proportion of each type of unit in the samples of residential projects was assessed.

The last dependent variable of this study is the land parcel attribute variable (Z_i). Land transaction information includes key indicators of land parcel, such as "land transaction year", "land price per mu", and "designated land use area for construction". To construct an empirical model that reflects the real market conditions of the year when the project acquired land, this study processed land parcel attribute variables that reflect the surrounding supporting facilities of the land parcels. Annual data were collected from Gaode Map (a leading provider of digital map content, navigation, and location service solutions in China) for the points of interest (POIs) related to the period from 2003 to 2022. The POIs around the land parcel were calculated using ArcGIS 10.4 software based on the map data of the year of land transaction. After a rigorous cleaning process of the empirical data, 1051 sample data were finally obtained and were included in the empirical analysis model, covering 369 residential developers involved in land selection and project development. The empirical variables and quantification methods are shown in Table 1. The descriptive statistics of the variables are presented in Table A1 in Appendix A.

Table 1. Empirical variables and quantification methods.

Variable	Definition	Quantification Method
Residential project feature variable (X_n)		
Green	Greenery rate	Residential green space area/total residential area (%)
FAR	Floor area ratio	Ratio of total residential construction area to land area
Park	Parking ratio	Number of parking spaces in the residential project/total number of households in the residential project
NOB	Number of buildings	Number of residential project building units
Area	Project land area	Residential project construction land area (square meters)
HP	Average transaction price	Average price of second-hand housing transactions in the residential project (CNY/square meter)
Prop_basic	Proportion of basic demand units	Proportion of units smaller than 90 m^2 in the residential project
Prop_med	Proportion of medium-sized units	Proportion of units with an area between 90 and 144 m^2 in the residential project
Prop_large	Proportion of large-sized units	Proportion of units with an area between 144 and 200 m^2 in the residential project
Prop_lux	Proportion of luxury units	Proportion of units larger than 200 m^2 in the residential project (including townhouses and duplexes)

Table 1. *Cont.*

Variable	Definition	Quantification Method
Land parcel attribute variable (Z_i)		
Dis_cbd	Distance to city center	Straight-line distance from the residential project to the nearest city center, including Hubin Business District, Wulin Square, Qianjiang New City, and Binjiang Science and Technology Park (meters)
Dis_nei	Distance to neighborhood	Straight-line distance from the residential project to the nearest other residential project (meters)
Dis_sub	Distance to subway station	Distance from the nearest subway station to the residential project site in the year of land acquisition (meters)
Dis_hos	Distance to top-tier hospital	Distance from the nearest top-tier hospital to the residential project site in the year of land acquisition (meters)
Dis_sch	Distance to key middle school	Distance from the nearest key middle school to the residential project site in the year of land acquisition (meters)
Num_mart	Number of supermarkets	Number of supermarkets (including hypermarkets, convenience stores, and general markets) within a 1 km radius of the residential project site in the year of land acquisition
Num_shop	Number of shopping centers	Number of shopping centers within a 1 km radius of the residential project site in the year of land acquisition
Num_park	Number of parks	Number of parks (including parks and park squares) within a 1 km radius of the residential project site in the year of land acquisition
Num_bus	Number of bus stops	Number of bus stops within a 0.5 km radius of the residential project site in the year of land acquisition
LP	Price per mu	Land transaction price per mu for residential developers (10 thousand CNY/mu), adjusted based on the consumer price index of the land transaction year and the base year (2022)

Note: The descriptive statistics of the variables are presented in Appendix A Table A1. "Mu" is a unit of land area commonly used in China; 1 mu is equal to 666.67 square meters.

3.2. Model and Methodology

The establishment of the model proposed in this study required the following assumptions to be formulated in advance. First, it was assumed that the "decision-maker" in the model is the developer, and all the unit characteristics within a residential project are the same. Second, the profit function was endogenously determined as a function of project characteristics and land parcels. Third, real estate developers have a profit-seeking behavior and will choose locations with the goal of maximizing their profits. Fourth, each developer will select the project site among all feasible locations within the study area. Fifth, the collected project data will generate a characteristic function related to the probability of choosing that submarket.

Referring to previous models proposed in relevant research [17,37,39], this study constructed an LCA model of developer location. First, according to the characteristics of housing projects, the potential categories of the housing market were identified. Then, according to the delimitation of the housing market, the determining factors of site selection of developers were analyzed. In this way, there was no need to define the housing market in advance, and developers can obtain land decision-making factors for different housing project types. This study assumed that developers would choose development sites with the goal of maximizing their own profits. The profit maximization formula for a developer who develops a project n in submarket s at location i is as follows:

$$max_{i\epsilon I}\pi_n(i|s) = R_{nis}(Z_i, X_n) - D_n(X_n) \quad (1)$$

where R_{nis} is the total revenue function of the developer's project development, D_n is the project development cost, and Z_i and X_n represent the land parcel attribute variables and the project characteristic variables, respectively. The specific functional form of R_{nis} in Equation (1) was expanded to facilitate the derivation of the following formula:

$$R_{nis} = \beta_s \cdot Z_i + \gamma_s \cdot X_n \quad (2)$$

The basic form of the discrete selection framework was expressed as follows:

$$P_n(i|s) = \frac{exp(\mu \cdot \pi_n(i|s))}{\sum_{j=1}^{J} exp(\mu \cdot \pi_n(J|s))} \ \forall n, i, s \quad (3)$$

where μ represents the scale parameter. To establish the proposed model, this study adopted a framework based on discrete choice modeling and probabilistic choice modeling to achieve the effect of submarket segmentation and selection. The final form of the proposed model is as follows:

$$P_n(i|s) = \frac{exp(\beta_s \cdot Z_i)}{\sum_{j=1}^{J} exp(\beta_s \cdot Z_j)} \ \forall n, i, s \quad (4)$$

where n, i, and s represent the residential project, the site selection of the residential project, and the submarket of the residential project, respectively.

Equation (4) was obtained by substituting Equations (1) and (2) into Equation (3). It represents the conditional probability that residential project n belonging to submarket s chooses location i for construction, with β_s as the vector of characteristic price parameters and Z_i indicating the land parcel attribute variable.

The membership function W_{ns} was introduced into the discrete selection framework [33]. The conditional probability formula to determine whether development project n belongs to submarket s is as follows:

$$P_n(s|X_n) = \frac{exp(W_{ns}(X_{ns}, \theta_s))}{\sum_{g \in S} exp(W_{ng}(X_n, \theta_g))} \ \forall s, n \quad (5)$$

where X_n is the characteristic variable of the developer's project, W_{ns} is the submarket membership function, and θ_s is the membership parameter.

By combining Equations (4) and (5), the parameters β_s and θ_s could be effectively estimated using the maximum-likelihood estimation method. The unconditional probability that developers will choose to develop residential project n at location i is expressed as follows:

$$P_n(i) = \sum_s P_n(i|s) \cdot P_n(s|X_n) \ \forall i, n \quad (6)$$

The membership parameter θ_s was used to label the unconditional probability of each project in the dataset belonging to a particular submarket, which was then imported into ArcGIS for visual analysis.

4. Potential Market and Land Selection for Residential Projects Development in Hangzhou

This section presents the specific process and the fitting results of the use of the LCA model. The fitting results of the latent class modeling are shown in Table 2. The Akaike information criterion (AIC), the Bayesian information criterion (BIC), and the adjusted BIC were used as the basis to measure the goodness of the model. Their calculation formula allows us to balance the explanatory power and the complexity of the model. Lower values entail a greater conciseness of the model; this helps select a more concise model with high explanatory power. Entropy is a measure of the uncertainty of category allocation in the model. A high entropy value (close to 1) means that the data points are clearly classified in their corresponding latent classes. Taking these parameters into account, this study determined five latent classes as the optimal potential market classification for the data. In addition, the category probabilities show that Latent Classes 4, 2, and 1 are the three major project development potential markets in the city.

Table 2. LCA model fit information.

Class	AIC	BIC	aBIC	Entropy	Class Probability
2	28,471.437	28,625.120	28,526.659	0.881	0.255/0.745
3	27,122.353	27,330.568	27,197.169	0.921	0.165/0.243/0.593
4	26,373.121	26,373.121	26,204.785	0.943	0.163/0.580/0.220/0.037
5	25,398.140	25,715.419	25,512.146	0.951	0.161/0.220/0.037/0.575/0.008
6	24,685.536	25,057.348	24,819.137	0.942	0.154/0.388/0.251/0.165/0.008/0.034

Note: AIC: Akaike information criterion; BIC: Bayesian information criterion; aBIC: adjusted Bayesian information criterion.

4.1. Residential Project Development Latent Class Division

The top half of Table 3 shows the coefficients of the determining factors for each category. Latent Class 1 emphasizes the configuration of basic demand housing units. The high floor area ratio, the low number of buildings, and the small land area of the projects reflect the high-rise characteristics of this class of projects. This type of housing was labeled as "high-rise concentrated basic demand residential development". Latent Class 2 typically has higher parking ratios and significantly higher average transaction prices, with large-sized units also accounting for a larger proportion. The residences in this class were labeled as "high-end improvement-type residential development". Latent Class 3 is characterized by a higher parking ratio and high average transaction prices, with a larger number of buildings and a lower floor area ratio. This indicates that these residences are designed for buyers who pursue a high-quality lifestyle. Therefore, this category was labeled as "luxury low-density residential development". Latent Class 4 is characterized by a high proportion of medium-sized units, low average transaction prices, and a low parking ratio. Therefore, this category was labeled as "primary improvement-type residential development". Latent Class 5 was labeled as "large-scale mixed-density residential development".

Table 3. Latent class and land selection of Hangzhou residential development projects.

	LC 1	LC 2	LC 3	LC 4	LC 5
Green	−0.147 [c] (0.081)	−0.060 (0.053)	0.033 (0.173)	0.022 (0.038)	3.087 [b] (1.325)
FAR	0.232 [b] (0.106)	−0.004 (0.057)	−0.559 [c] (0.238)	−0.012 (0.039)	−1.238 [a] (0.281)
Park	−0.433 [a] (0.062)	0.439 [a] (0.092)	0.658 [a] (0.216)	−0.089 [b] (0.035)	−0.345 [a] (0.088)
NOB	−0.292 [a] (0.036)	0.066 (0.054)	0.528 [a] (0.188)	−0.038 (0.035)	4.555 [b] (1.913)
Area	−0.147 [b] (0.061)	−0.186 [a] (0.036)	−0.082 (0.097)	0.023 (0.030)	7.367 [a] (1.434)
HP	−0.585 [a] (0.060)	1.150 [a] (0.086)	0.460 [b] (0.186)	−0.312 [a] (0.041)	−0.505 [b] (0.229)
Prop_basic	2.020 [a] (0.091)	−0.516 [a] (0.011)	−0.462 [a] (0.046)	−0.349 [a] (0.020)	0.479 [b] (0.240)
Prop_med	−0.625 [a] (0.059)	−1.100 [a] (0.095)	−1.091 [a] (0.158)	0.687 [a] (0.040)	−0.022 (0.276)
Prop_large	−0.814 [a] (0.030)	1.520 [a] (0.089)	−0.497 [a] (0.150)	−0.329 [a] (0.042)	−0.701 [a] (0.098)
Prop_lux	−0.086 [c] (0.051)	−0.076 (0.053)	4.018 [a] (0.429)	−0.217 [a] (0.024)	0.752 [c] (0.392)
	LC 1	LC 2	LC 3	LC 5	LC 4 (BNL)
Dis_cbd	−1.863 [a] (0.219)	0.057 (0.152)	0.251 (0.323)	−0.624 (0.654)	0.507 [a] (0.123)
Dis_nei	−0.066 (0.125)	0.161 (0.125)	0.207 [c] (0.114)	0.269 (0.231)	−0.125 [c] (0.067)
Dis_sub	1.194 [a] (0.205)	−0.176 [c] (0.186)	0.275 (0.284)	0.370 (0.590)	−0.456 [a] (0.120)
Dis_hos	0.585 [a] (0.165)	−0.564 [b] (0.250)	−0.406 (0.360)	−0.368 (0.372)	−0.085 (0.125)
Dis_sch	−0.189 [c] (0.103)	0.134 (0.128)	0.210 (0.180)	−1.039 [b] (0.514)	0.056 (0.078)
Num_mart	0.004 (0.022)	−0.024 (0.017)	−0.024 (0.040)	−1.104 [b] (0.499)	0.020 (0.014)
Num_shop	0.195 (0.131)	0.159 (0.115)	0.027 (0.216)	1.332 [b] (0.633)	−0.164 [a] (0.096)
Num_park	0.072 (0.067)	−0.025 (0.053)	−0.221 (0.171)	0.133 (0.459)	−0.033 (0.042)
Num_bus	0.075 [b] (0.032)	−0.001 (0.031)	−0.012 (0.070)	−0.201 (0.186)	−0.037 (0.024)
LP	−0.468 [b] (0.228)	1.371 [a] (0.146)	0.905 [a] (0.327)	−5.626 [a] (2.105)	−0.747 [a] (0.097)
_cons	−2.286 [a] (0.208)	−1.444 [a] (0.167)	−2.455 [a] (0.307)	−7.889 [a] (2.649)	0.406 [a] (0.114)
Log-Likelihood		−888.563			−638.016
Wald χ^2		339.500			121.24
p value		0.000			0.000

Note: The variable estimates are indicated above the brackets, while the standard errors are indicated within brackets; a, b, and c indicate the significance levels of the variables at the thresholds of 1%, 5%, and 10%, respectively.

4.2. Decisions on Land Site Selection for Residential Project Development

This subsection explores the influence of land parcel attributes (Zi) on location choices for different residential market types at the time of land acquisition. Using the sample from "Model 2" in Table 2, Latent Class 4, the largest group, was chosen as the reference. A binary logit model (BNL) was additionally used to analyze the location characteristics of

Class 4 by setting a binary variable to indicate if a project belongs to this class. The results of the different types of land selection are shown in the lower part of Table 3.

Latent Class 4 (“primary improvement-type residential development”): These projects are located away from city centers and are characterized by less commercial activity and lower land prices. Proximity to rail transit, such as subways, compensates for the distance from the CBD. Aimed at homebuyers seeking affordable upgrades, these developments prioritize cost–performance, with lower parking ratios reflecting the smaller number of private cars.

Latent Class 1 (“high-rise concentrated basic demand residential development”): Developers select land near city centers with mature communities. They prefer lower-priced plots, balancing cost with proximity to employment and schools, even if they lack subway access or top-tier medical facilities.

Latent Class 2 (“high-end improvement-type residential development”): Developers choose higher-priced land, focusing on future profitability. These projects prioritize proximity to quality resources, such as subways and hospitals. Moreover, they are less dependent on rail transit, as a higher parking ratio meets residents’ travel needs.

Latent Class 3 (“luxury low-density residential development”): Developers target plots with fewer adjacent communities to maintain exclusivity. They pay premium prices, expecting that the unique location will attract buyers willing to pay for high-quality living.

Latent Class 5 (“large-scale mixed-density residential development”): These projects offer diverse unit designs to meet a broad range of buyer needs. Developers focus on affordable housing and prioritize proximity to shopping centers and educational resources to support a large community.

5. Discussion and Implications

5.1. The Spatial Distribution of Potential Markets for Urban Residential Projects

In this study, ArcGIS was employed to conduct a detailed analysis of the spatial distribution of different types of residential projects in Hangzhou, using the inverse distance weighting (IDW) interpolation method. This method was used to create a probability heatmap of the urban spatial distribution of projects. The spatial distribution of the various project types is shown in Figure A1 in Appendix A.

In terms of overall urban situation, Latent Class 1 (“high-rise basic demand residential development”) and Latent Class 2 (“high-end improvement-type residential development”) have a higher probability of being located in the central areas of the main urban district. This distinct spatial characteristic reflects the city’s urban planning strategy. Basic demand housing tends to cluster around old urban centers, catering to residents’ needs for convenience and proximity to employment opportunities. Because the old city is more densely built, these residential projects do not occupy a large area and have fewer buildings. In contrast, Latent Class 2 (“high-end improvement-type residential development”) is highly concentrated along the northwest bank of the Qiantang River and in emerging districts, such as Qianjiang New City and Yuhang Future Science and Technology City. This pattern illustrates Hangzhou’s commitment to a “polycentric urban development” strategy, where high-end projects are typically situated in new commercial hubs, enhancing accessibility and attracting affluent residents.

In parallel, “primary improvement-type residential” projects are increasingly distributed across non-core areas, while luxury developments are more frequently found on the periphery, often adjacent to scenic locations. Additionally, large-scale mixed-density projects are planned in the suburbs to alleviate residential density in the central areas. This layered approach to urban development not only addresses diverse housing needs but also promotes a balanced growth throughout the whole city of Hangzhou, ensuring that all residents can benefit from the city's ongoing transformation.

5.2. The Coefficient of Developers' Willingness to Pay (WTP) for Land Selection

As key participants in the land market, residential developers assign different values to various land characteristics. Based on Model 2 in Table 2, the regression coefficient of the variable "price per mu $*IF^{-1}$" was used as the benchmark for price attributes, and the coefficients of each plot feature were considered as non-price attributes. The willingness-to-pay (WTP) coefficient is an economic measure of the maximum price that consumers are willing to pay for a good or service. As such, it reflects the consumer's demand and value for that good or service [28,37]. In this study, the WTP was calculated as follows:

$$WTP = \pm(\beta_{attribute}/\beta_{price}) \quad (7)$$

where $\beta_{atrribute}$ is the regression coefficient for non-price attributes and β_{Price} is the regression coefficient for the price attribute.

Table 4 presents the coefficients of the WTP of developers for each potential project type; the coefficients in bold indicate the WTP corresponding to variables that are statistically significant for each category of housing. When constructing "high-rise concentrated basic demand residential development", developers show a strong WTP for plots close to the city center, key middle schools, and with a high number of bus stops. Specifically, the developers' WTP for plots near the city center was found to be 9.854 times that for plots near key middle schools, and 24.881 times that for plots with a high number of bus stops, respectively. This indicates the developers' belief that, for basic-demand-type residential projects, a location near the city center is particularly important, as it directly meets the living needs of the target residents. Since the Chinese Politburo meeting in 2019, the real estate market has adopted a development policy aimed at securing basic needs and has introduced the "Nine Quality Standards for Basic Demand Housing", emphasizing the development concept of ensuring that each community is within a 30 min living circle of the city center and is equipped with educational resources. The empirical results of this study show that Hangzhou's residential developers comply with this high-quality standard when developing basic demand housing.

Table 4. Developers' WTP coefficients for various types of development.

	Latent Class 1	Latent Class 2	Latent Class 3	Latent Class 4	Latent Class 5
Dis_cbd	**−3.981**	0.042	0.277	**0.679**	−0.111
Dis_nei	−0.141	0.117	**0.229**	**−0.167**	0.048
Dis_sub	**2.551**	**−0.128**	0.304	**−0.610**	0.066
Dis_hos	**1.250**	**−0.411**	−0.449	−0.114	−0.065
Dis_sch	**−0.404**	0.098	0.232	0.075	**−0.185**
Num_mart	0.009	−0.018	−0.027	0.027	**−0.196**
Num_shop	0.417	0.116	0.030	**−0.220**	**0.237**
Num_park	0.154	−0.018	−0.244	−0.044	0.024
Num_bus	**0.160**	−0.001	−0.013	−0.050	−0.036

Notes: The values in the table represent the changes in developers' willingness to pay when there is a 1% change in the corresponding land location characteristics. The numbers in bold indicate that the variable is significant.

Combining the results of Latent Class 2 and Latent Class 4, it can be seen that when developing a "high-end improvement-type residential development", developers are willing to pay 1.28 thousand CNY/square meter and 4.11 thousand CNY/square meter for a reduction of one unit in the distance to subway stations and to top-tier hospitals, respectively. Especially, the latter's WTP is 3.211 times that of the former, which confirms that top-tier hospitals are considered by developers to be the most important factor in attracting high-end residential groups. When developing a "primary improvement-type residential development", developers are willing to pay 6.10 thousand CNY/square meter to improve the distance to subway stations, a value that is higher than for "high-end improvement-type residential development". This finding indicates that, as a cost-effective choice for first-time replacement households, developers will focus on investing in the convenience of rail transit to enhance the commuting capabilities of residents. For high-end residents, although rail transit is still valued as a high-quality municipal facility, developers will correspondingly reduce their investment in rail transit resources, due to their strong private transportation capabilities.

This study adopted the perspective of residential developers on the supply side and categorized the Hangzhou residential development market into five residential development submarkets based on project characteristics. This classification is more comprehensive and rational than that proposed by previous studies, which only divided submarkets based on single indicators, such as administrative regions and residential prices [40]. Moreover, the adoption of this method of categorization also confirms that housing submarkets do not necessarily maintain complete independence and continuity in space [17]. Furthermore, by using geographic location, land prices, investment returns, and supporting facilities as variables, this study analyzed developers' preferences for location selection when developing projects with different grades. The results of this study on variables such as location conditions and supporting facilities, which have a significant impact on land selection, were highly consistent with those of existing research on factors affecting land prices [41]. Moreover, the detailed exploration of different types of residential projects, performed by the present study, provides a new dimension for research on urban spatial layout and land use, and increases the understanding of supply-side behavior in the real estate market. The spatial distribution of luxury housing and improvement housing, identified in this study, is spatially coupled with the residential distribution of middle- and high-income households revealed by Zhang et al. [42] from the perspective of demand.

5.3. Differences in Land Payment Willingness of Different Types of Developers

During the land allocation process in Chinese cities, the government has informal preferences for different types of developers. Thanks to their close relationship with the government, state-owned developers can more easily obtain undisclosed information and government-controlled bank funds. In contrast, private enterprises confront a more disadvantageous political environment and financial constraints. This typically results in the fact that state-owned developers are willing to offer higher premiums in land auctions compared to private developers [43,44].

This study analyzed the equity structure of 369 developers within the sample and categorized them as either state-owned enterprises or private enterprises. The former were defined as developers with a state-owned capital ratio exceeding 50%. The choice of this threshold was justified by the consideration that when the proportion of state-owned capital is less than 50%, the state does not possess absolute controlling rights. In parallel, private enterprise developers were defined as those enterprises with a proportion of state-owned capital equal to zero. By modeling the influencing factors of land acquisition for the sub-samples, it was discovered that state-owned developers tend to have higher unit prices and acquire larger-scale land. This might be associated with their lower financing costs and more stable capital chains. In contrast, being affected by high financing costs, private developers are more inclined to acquire smaller-scale land. Subsequently, the LCA model was separately employed for estimation for each sample. Due to space constraints, the detailed regression results on the classification are not included in this manuscript and can be provided upon request. Table 5 shows the willingness coefficient of the two types of developers to pay for land. The results indicate a greater propensity of state-owned developers towards the high-end residential market. In fact, the proportion of their high-end improvement type and primary improvement type was 46% and 35%, respectively. In contrast, for private enterprises, the proportion of these two types was 23% and 56%, respectively. State-owned developers were found to be more inclined to undertake high-end improvement projects in urban center locations, with a willingness-to-pay coefficient of 0.3, while the corresponding payment coefficient for private developers was 0.058. In the case of primary improvement residential projects, private developers were found to be more willing to pay for those in proximity to subway stations, with a willingness-to-pay coefficient of 0.55, which was higher than that of state-owned developers (0.39). For both types of developers, high-end improvement residential projects were positively correlated with higher land prices, while the demand-driven residential or primary improvement residential projects were negatively correlated with land prices.

Table 5. WTP coefficient of the two types of developers for various types of projects.

	State-Owned Developer					Private Developer				
	LC1	**LC2**	**LC3**	**LC4**	**LC5**	**LC1**	**LC2**	**LC3**	**LC4**	**LC5**
Dis_cbd	-	**0.634**	−0.224	**−0.300**	**0.554**	-	−0.174	**−0.058**	-	**0.838**
Dis_nei	-	0.088	0.085	0.000	−0.566	-	0.063	0.150	-	**−0.225**
Dis_sub	-	0.005	**−0.387**	0.066	0.242	-	0.069	−0.205	-	**−0.546**
Dis_hos	-	**−1.128**	**0.735**	**−0.656**	**−0.614**	-	−0.058	−0.309	-	−0.324
Dis_sch	-	0.088	−0.035	0.146	0.062	-	**−0.202**	0.064	-	0.173
Num_mart	-	−0.034	**0.056**	−0.025	**−0.074**	-	**−0.223**	−0.011	-	0.017
Num_shop	-	0.565	**−0.645**	**0.515**	0.127	-	**0.251**	0.099	-	−0.221
Num_park	-	0.144	−0.130	0.036	−0.121	-	0.014	−0.006	-	−0.057
Num_bus	-	−0.007	−0.039	−0.016	−0.037	-	−0.038	−0.007	-	−0.043

Notes: For state-owned enterprise developers, LC1–LC5 indicate the rigid demand type, the high-end improvement type, the primary improvement type, the high-rise residential concentration high-end improvement type, and the luxury type, respectively. For private enterprise developers, LC1–LC5 indicate the high-rise concentrated basic demand type, the large-scale low-density type, the high-end improvement type, the compact luxury high-end improvement type, and the primary improvement type, respectively. Numbers in bold indicate that the variable is significant.

6. Conclusions

Against the backdrop of a declining real estate market and a tightening policy environment, the development prospects of real estate developers are facing severe challenges [4]. Therefore, real estate companies need to adopt cautious market positioning and land acquisition strategies, deeply understand the differences across urban residential markets, and formulate refined development strategies to meet market demands, optimize returns, control costs, and improve their financial conditions. Unlike a large number of existing studies, such as Balta and Öztürk [45] and Ibraimovic and Hess [37], which mainly focused on the demand side of the real estate market, this study adopted a novel perspective, exploring the residential space distribution and the location choice behaviors of residents. This study discussed the multidimensional development of the real estate market from a developers' perspective. By applying the latent class model, this study classified land acquisition projects in Hangzhou from 2003 to 2020 and explored the location selection factors for different types of projects, using ArcGIS and WTP coefficients to assess the land selection strategy of developers.

This study divided the Hangzhou residential development market into five potential markets based on price, unit type ratio, location, and community building characteristics: "high-end improvement-type residential development", "high-rise concentrated basic demand residential development", "primary improvement-type residential development", "luxury residential development", and "large-scale mixed-density residential development". It was found that primary improvement, high-end improvement, and basic demand housing are the three major markets in the city (in descending order of importance). At present, the development proportion of "basic demand type" housing is still relatively low. To implement the national development strategy of securing basic needs, developers should appropriately increase the proportion of basic-demand-type housing development, while relevant departments should also increase subsidies for the construction of basic demand housing to ensure the profits of developers. Compared to Cox and Hurtubia's [17] classification of urban expansion areas into mainstream submarkets and exceptional submarkets based on potential characteristics, the residential housing market identified in this study is more diversified in level and in line with the characteristics and policy background of China's housing market.

These five types of projects correspond to different site selection characteristics. The results of the calculation of the WTP coefficients indicate that residential developers in Hangzhou consider top-tier medical resources to be an important asset targeting high-end consumer groups. The development of the basic-demand-type of housing follows the national priority of securing basic needs, ensuring its proximity to city centers and a convenient access to educational resources. For primary-improvement-type housing, developers showed to focus on investing in rail transit resources to enhance their cost–performance ratio and mitigate unfavorable location conditions. For real estate development projects, the early stage of land acquisition and product positioning is crucial, as it directly affects project sales and investment profits. This study established a connection between these two elements, and the results also confirmed that different types of projects have different demands for land location conditions. Developers should select suitable land for their development according to their corporate development strategy and product strategy. In passive situations, they should conduct appropriate project positioning based on land characteristics in order to meet the needs of different customer groups.

Different types of housing have different spatial clustering characteristics. The results of the analysis of the project's city distribution map and heatmap showed that Hangzhou's residential development market presents a concentric layout. High-end-improvement-type residences and basic-demand-type residences are concentrated in the city center area, occupying the emerging core business districts and the old city center area, respectively. Primary-improvement-type housing is mainly distributed in the non-core areas of the main urban area, compensating more cost-effective housing with relatively unfavorable location conditions. Luxury-type housing is mainly constructed on the outskirts of the main urban area, so as to meet the needs for an independent space pursuing a high-quality lifestyle. Large-scale project developments are also located in the area ranging from the outskirts of the main urban area to the suburbs of the city, aiming to alleviate the residential pressure in the main urban area. Overall, Hangzhou's residential development market presents a diversified and balanced development situation. This provides a basis for government departments to formulate urban land use plans and optimize the configuration of public services. In the core urban area, through urban renewal, it is necessary to further improve the urban interface and the natural and cultural environment of the old city area, mitigate urban traffic congestion by opening up urban branch roads, optimize bus routes, and increase the density of the subway network, so as to provide a better regional environment for basic-demand-type housing and high-end improvement housing. In non-core areas, it is necessary to further improve the accessibility of subways and increase commercial and educational support, so as to redirect the dispersion of residents and alleviate the population and residential pressure in the core urban area. Due to the limited data acquisition channels of residential developers, in this study, the types of developers have not been thoroughly addressed. The gathering of additional information on the finance and management of developers would allow for a detailed investigation of the classification of enterprises with different sizes or brand influence. Due to the frequent regulation and control policies of the real estate market during the study period, it was difficult to quantify various requirements on land supply. As a result, this study only reflects the impact of land policies through land prices. In the future, the impact of land policies should be further investigated through the choice of appropriate research periods and sample selection.

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Appendix A

Table A1. Descriptive statistics of variables.

Variable Name	Mean	Median	Std.Dev	Min	Max
Green	31.254	30.000	4.129	2.000	70.000
FAR	2.408	2.400	0.630	0.530	7.300
Park	1.137	1.070	0.379	0	5.030
NOB	23.193	14.000	31.408	1.000	592.000
Area	51,644.330	41,666.670	46,499.300	2337.455	72,4637.700
HP	25,812.550	23,214.000	13,439.970	5245.000	72,029.000
Prop_basic	0.118	0	0.216	0	1.000
Prop_med	0.493	0.502	0.295	0	1.000
Prop_large	0.326	0.247	0.294	0	1.000
Prop_lux	0.063	0	0.144	0	1.000
Dis_cbd	11,624.180	10,171.120	7342.383	72.687	38,483.580
Dis_nei	435.934	296.950	500.302	15.128	6448.444
Dis_sub	6111.758	3799.531	6363.247	75.149	38,270.280
Dis_hos	7355.731	5007.190	6626.459	142.956	37,644.180
Dis_sch	4079.731	3519.299	2936.987	122.758	27,115.970
Num_mart	6.487	5.000	6.580	0	38.000
Num_shop	0.360	0	0.891	0	8.000
Num_park	1.007	0	1.909	0	21.000
Num_bus	3.537	3.000	3.458	0	30.000
LP	2281.069	1760.373	1800.603	81.667	10,083.830

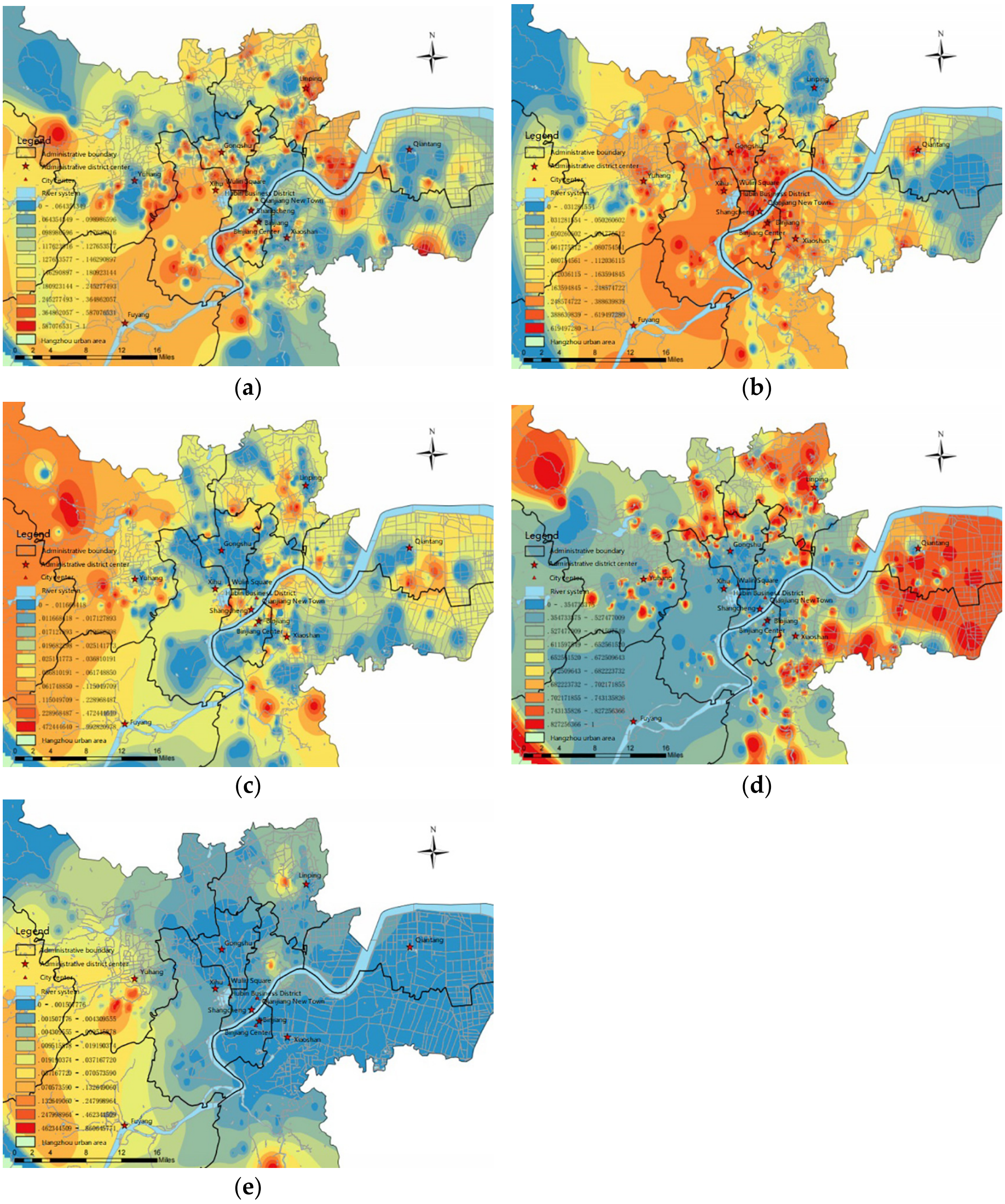

Figure A1. Probability heatmap of residential development distribution in Hangzhou. Notes: (**a**) High-rise concentrated basic demand residential development; (**b**) high-end-improvement-type residential development; (**c**) luxury residential development; (**d**) primary-improvement-type residential development; and (**e**) large-scale mixed-density residential development. Warmer colors represent higher-probability areas, while colder colors represent lower-probability areas.

Note

1 According to the deed tax collection standards issued by the State Administration of Taxation and the Ministry of Housing and Urban Rural Development in 2016, residential properties under 90 square meters are eligible for a low tax rate. The State Council's 2005 notice "Opinions on Doing a Good Job in Stabilizing Housing Prices" stipulates that the standard for ordinary housing should not exceed 144 square meters. In light of the actual situation of the housing market, luxury residences above 144 square meters are further divided into large and luxury types with 200 square meters as the boundary.

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