Variance analysis and linear regression: Exploring the impact of location factors on the average logarithmic price of pre-owned housing in Shenzhen

Yunzhong Ding[1,4], Zehua Tang[2], Minjia Wang[3]

[1]College of Arts and Sciences, University of North Carolina at Chapel Hill, NC, 27599-3140, USA
[2]School of Electrical Engineering, Suihua University, Suihua,152001, China
[3]Shenzhen College of International Education, Shenzhen, 518000, China

[4]dingding@ad.unc.edu

Abstract. The primary purpose of this report is to investigate the impact of locational factors on the average prices of second-hand homes in Shenzhen, providing a theoretical foundation for the pricing of such properties. To achieve this, the report first establishes indicators to describe the characteristics of second-hand homes. Then, it constructs an analysis of the variance model to explore the impact of multiple related factors on housing prices regarding the average logarithmic price of pre-owned housing in Shenzhen. The model results indicate significant correlations between administrative divisions, whether the property is in a school district, the orientation of the house, the age of the house, and the area with the logarithmic price per unit area of second-hand housing. At the end of the report, two inter-complimentary multivariate linear regression models are constructed, and simulated data produced through R studio are also provided, and the final model is used for practical application to accurately predict the price of second homes under the appropriate conditions.

Keywords: Average logarithmic price, multivariate linear regression, Shenzhen

1. Introduction

There has never been any doubt that the real estate industry has long been a decisive factor in pivoting the direction of China's economy. Indeed, it would be an understatement to delineate such a vital industry consisting of real estate firms resembling an extensive range of the economic spectrum as the pillar of China's economy; many would instead refer to the industry as the heart and soul of China. Yue Geng, a researcher at Anhui Business College of Vocational Technology, depicted the trend of real estate value fluctuation in the Modern Business Trade Industry Journal through a bird's eye view over the past decade. She stated that since China implemented the housing system reform in the country in 2003, the average sale price of commercial-based residential buildings has grown at an annual rate of about 8.6% from 2003 to 2020. Though the momentum for further price inflation was undoubtedly hindered by the devastating side effects of the COVID-19 pandemic on the economy and trade, housing costs have unexpectedly experienced an anomalous uptick in certain regions of China despite the economic and political sabotage toward private-owned real estate companies under the epidemic prevention policies, according to the National Bureau of Statistics [1]. To promote the real estate market after abolishing the epidemic prevention policies and to meet the housing needs of many internally migrant workers, as well as to address the issue of stock housing in major metropolitan areas, the state introduced the "mortgage transfer" policy, which significantly boosted the pre-owned housing transaction market. Real estate expert Li Xie interpreted this policy and believed that compared to traditional transaction modes, "mortgage transfer" is able to save a significant portion of transaction costs for both parties, greatly promoting the real estate market's mobility and fluidity [2].

Under the notion of nationwide stimulus, Securities Times reporter Da stated that with cities like Beijing, Shanghai, and Shenzhen loosening their corresponding purchase restrictions before the Spring Festival holidays of 2024, according to transaction volume data reflected by the Shell Research Institute, Shenzhen's transaction volume doubled compared to last year among major cities [3]. Such inclination of transaction rebound demonstrated that China's overall pre-owned housing transaction market is improving. Sensing and conceptualizing the revival of China's pre-owned real estate market, Zhang, along with other research members for Securities Times, intended to investigate the factors determining the price of second-hand housing in Shenzhen microscopically. Then, they sought to establish a practical model for solving the low-cost-effectiveness issue among local residents. In reality, the relationship between determining factors toward the housing price is far more complicated than a simple skeletal model. For instance, real estate researcher Wei Mi proposed that second-hand housing without elevators could potentially be more expensive than those with elevators under the same conditions [4]. Similarly, Yantai researcher Yu Guo discovered that the housing age and the unit price of second-hand housing are positively and closely correlated, with prices increasing as the housing ages, considering the rest of the conditions being identical [5]. By analyzing the data of about 1500 sets of second-hand houses in Haidian District, Beijing, Ke concluded that the unit price of second-hand houses facing south is slightly higher than that of non-southern houses [6]. As the most convenient way of urban transportation in today's society, the subway has become the first choice in most urban transportation planning. In view of this factor, Zhong took Nanchang Subway Line 1 as the research object and concluded that the second-hand house price in the residential community near the subway station was higher than the second-hand house price in the local area [7]. By analyzing the data of about 12,400 second-hand houses in 8 districts of Nanjing and establishing a multiple regression model affecting the housing price per unit area, Liu Bing et al., Nanjing Polytechnic Institute of Industry, concluded that for every increase in the number of bedrooms, the housing price per unit area increased by 401.1 yuan, and the housing price per unit area with a living room was 2152.5 yuan higher than that without a living room [8]. In order to explore the impact of middle school districts on the second-hand housing prices of surrounding communities, Liang Liyu et al., Peking University, analyzed the data of 185 residential communities in three major urban areas of Shenzhen and concluded that the school entrance rate, teachers with master's degree or above and key schools had a positive boost effect on the second-hand housing prices of surrounding middle schools [9]. In the analysis of influencing factors of second-hand house price based on the GWR model, Feng et al. came to the following conclusion: The overall second-hand house price in Chengdu is gradually decreasing from the center of the concentric circle to the outside, and the prices of Wuhou district, Jinjiang District, Qingyang District and other districts in the city center are generally higher than others [10].

Acknowledging the abovementioned factors, this paper seeks to investigate further the correlation between the pre-owned housing price in Shenzhen, a metropolitan city less than 17 miles from Hong Kong, and physical factors regarding such residential areas through the research. This paper will be collecting data through real estate companies in China that are responsible for the city of Shenzhen. Then, this paper will analyze the correlation between the average price of pre-owned residential buildings and potential determining factors. These factors include but are not limited to the availability of subway-based transportation, the school district of the location, coastal status, the elevator-household ratio, direction of the windows, mall availability, the size of the residential area, the age of the building, and the construction status. Through variance analysis and linear regression, this paper seeks to establish the own skeletal model that is capable of predicting the price for a pre-owned residential home through given information regarding the house. Such a model's versatility spans from helping a household locate proper housing regarding one's need to visualizing the trend for price fluctuation in the city of Shenzhen and other cities around the world, given sufficient data. The significance of these benefits lies in saving time during the house research process, enhancing the accuracy of the building corresponding to one's demand, and providing individual households with more options when considering purchase.

2. Methodology

2.1. Data source

The report obtained 3,000 simulated valid data points by adding random noise. Instead of using the direct sale price as the dependent variable, the report employs the logarithmically transformed sale price (referred to as "logarithmic price") for the following reasons.

Classic statistical theory suggests that the range of the dependent variable in regression analysis should be infinite in both directions (positive and negative). Although the sales price of second-hand houses cannot be negative, logarithmic transformation theoretically allows for such negative values. After logarithmic transformation, the data appears more Gaussian, with fewer extreme values.

2.2. Variable description

The most crucial reason for the logarithmic transformation is that it converts absolute differences into relative differences. For example, a difference of 0.10 has a different implication on the original scale compared to the logarithmic scale. If it's on the original scale, a difference of 0.10 represents a difference of 0.1 million CNY/m^2, which is difficult to interpret without context. However, on the logarithmic scale, 0.10 units reflect a proportional difference between the two original prices, offering a more meaningful interpretation of the data variance (Figure 1).

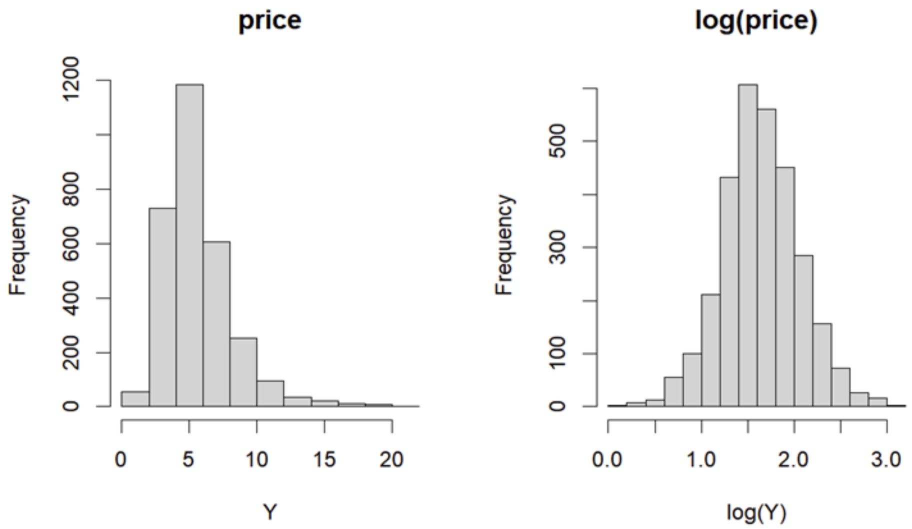

Figure 1. Original Scale & Logarithmic Scale of Price.

After establishing the logarithmic price as the dependent variable for this report, the next step involves considering the explanatory variables. Based on practical marketing experience, numerous factors can influence the price of second-hand houses, such as distance from the city center, transportation convenience, medical resources, and shopping and entertainment facilities. These factors help provide a more detailed description of second-hand housing and can serve as explanatory variables. Due to data limitations, the report could only collect data from the ten central administrative districts of Shenzhen. The variables were chosen based on location factors (administrative division, proximity to subway, sea view, school district availability) and structural factors (property area, house orientation, presence of an elevator, and renovation status). As the age of the house couldn't be used directly, it was

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categorized as follows: 0-5 years as new houses, 5-10 years as relatively new houses, 10-15 years as middle-aged houses, 15-20 years as older houses, and over 20 years as old houses (Table 1).

Table 1. Variable introduction.

Type		Name	Description	Value range
Dependent		Logarithmic price	Unit: 10,000yuan /m2	0.173~3.066
Explain	Location factor	Administrative division	Qualitative variables: 10 levels	Bao’an, Dapeng, Futian, Guangming, Longgang, Longhua, Luohu, Nanshan, Pingshan, Yantian
		Sea view room	Qualitative variables: 2 levels	1 means sea view room; 0 means no ocean view
		School district housing	Qualitative variables: 2 levels	1 represents the school district housing; 0 means not school district housing
		Subway	Qualitative variables: 2 levels	1 represents the proximity to the subway; 0 means not near the subway
	Structure factor	Area of house	Unit: m2	14~304
		Orientation of house	Qualitative variables: 2 levels	1 means the house faces south; 0 means that the house does not face south
		Age of house	Qualitative variables: 5 levels	New house, relatively new house, middle-aged houses, as older house, older houses
		Renovation	Qualitative variables: 2 levels	1 means the house has been renovated; 0 means that the house is not renovated
		Elevator	Qualitative variables: 2 levels	1 means there is an elevator; 0 means no elevator

2.3. Location factor - administrative division

In dissecting the intricate web of factors influencing second-hand housing prices in Shenzhen, the administrative division where a property is located emerges as a pivotal element. This study encompasses a nuanced examination of ten distinct administrative regions in Shenzhen: Bao’an, Dapeng, Futian, Guangming, Longgang, Longhua, Luohu, Nanshan, Pingshan, and Yantian, each boasting its unique geographical and policy nuances that could sway housing valuations. Nanshan stands out as Shenzhen’s vibrant high-tech crucible, a magnet for an array of tech behemoths, fostering a dynamic job market and a robust infrastructure. This aspect invariably colors the real estate landscape within its bounds. Futian, the city’s financial nucleus, anchors Shenzhen’s administrative heart and clusters a wealth of financial institutions and CBDs, weaving a rich and desirable fabric of urban living. Navigating through these administrative divisions provides a kaleidoscope of regional attributes, each weaving its influence on the fabric of second-hand housing prices in Shenzhen, a narrative central to this investigation.

2.4. Location factor - school district housing

Consider two properties situated in the same administrative district and with identical access to subway facilities. Would their average logarithmic prices be the same? Not necessarily. The market delineates a stark contrast between the prices of school district properties and non-school district ones. Take, for instance, a school district property in the Futian district that might fetch a price of 21,000 CNY per square meter, whereas a similar non-school district property in the vicinity might only command about 8,000 CNY per square meter. Despite the steep prices, school district properties, with their access to superior educational resources, remain highly coveted by parents, often selling much quicker than their non-school district counterparts. For the purposes of this report, this variable is binary: yes or no, indicating whether a property is in a school district or not.

2.5. Location factor – sea view properties

Similar to the impact of being in a school district, there is a significant price disparity between properties with and without a sea view. Even when other conditions are similar, a property with a sea view in the Nanshan district can reach a peak price of 19,000 CNY per square meter, while a non-sea view property might only go up to 14,000 CNY per square meter. This price difference underscores the economic value of proximity to the sea. In this study, this variable is dichotomous: a property either has a sea view (“yes”) or does not (“no”).

2.6. Location factor - proximity to subway

This indicator distinguishes between properties based on their access to subway transportation. In modern urban living, efficient transportation is indispensable, particularly in cities like Beijing, which is known for its traffic congestion, where the subway serves as a reliable means of public transport. Hence, the primary aspect of convenient transportation could well be the proximity to a subway station. Properties located near subway stations offer the advantage of reduced travel times, which typically translates into higher market values compared to properties without nearby subway access. However, quantifying this price difference requires precise data analysis. In this report, the proximity to the subway is categorized simply as “yes” or “no,” indicating whether a property is near a subway station.

2.7. Structural dynamics

Moving beyond the geographical attributes, the inquiry delves into the fabric of the property itself, exploring a suite of structural variables that are intrinsic to the dwelling and independent of its locale. These elements-encompassing the property’s vintage, its spatial footprint, orientation, renovation status, and the presence of an elevator-each tell a story that resonates with potential buyers in different ways. Consider the square footage, a primary metric that often dictates a buyer’s decision. The data spectrum reveals a fascinating range: the most compact abodes measure a mere 14 square meters, while the most expansive sprawl is over 304 square meters. The popular choice, however, gravitates towards a sweet spot ranging from 50 to 100 square meters, underscoring a common preference that balances spaciousness with manageability. Then there’s the age of the property-a narrative in itself. While the charm of a seasoned home might appeal to some, concerns about durability and modern conveniences often tip the scales in favor of newer constructions. Yet, these fledgling structures sometimes trade legacy for location, finding themselves distanced from the venerable institutions and infrastructures that lend a neighborhood its character. Through this lens, the author aims to dissect the nuanced interplay of these structural factors, offering a granular perspective on how they collectively sculpt the market valuation of second-hand residences.

3. Results and discussion

3.1. Descriptive analysis

Moving forward, this report will undertake a detailed descriptive analysis of the various explanatory variables. Having previously examined the property area, the focus now shifts to the categorical explanatory variables, mainly administrative divisions. The dataset is segmented into ten distinct groups corresponding to different districts, facilitating a nuanced statistical examination of each group’s dependent variable, as detailed in Table 2. Insights from Table 2 reveal a stark disparity in property prices across districts. Futian stands out with the highest logarithmic price of approximately 3.066, translating to an original price of around 21,500 CNY per square meter. Conversely, Longhua is the most economical district, with a logarithmic price near 0.173, equating to roughly 1,180 CNY per square meter. A comparative analysis of both mean and median values underscores that Futian and Nanshan are the priciest districts, while Dapeng and Pingshan are the most affordable, with other districts positioned at intermediate levels and exhibiting slight variations.

Table 2. District Data.

District	N	MU	SD	MIN	MED	MAX
Bao'an	398	1.724	0.305	0.696	1.690	2.772
Dapeng	240	1.052	0.309	0.287	1.029	2.077
Futian	397	1.949	0.322	0.872	1.913	3.066
Guangming	240	1.528	0.252	0.627	1.561	2.098
Longgang	240	1.437	0.267	0.657	1.413	2.041
Longhua	300	1.720	0.358	0.173	1.749	2.591
Luohu	300	1.573	0.329	0.531	1.545	2.521
Nanshan	405	2.077	0.337	1.308	2.053	3.005
Pingshan	240	1.277	0.179	0.607	1.285	1.903
Yantian	240	1.520	0.248	1.049	1.464	2.534

Applying the same analysis method previously for district variation, the study examines how property values are influenced by age, location, and features. Older properties in central areas, south-facing homes in Shenzhen, and properties in school districts command higher prices. Sea views and proximity to subway stations significantly increase value. Elevators and renovations also boost prices, reflecting preferences for convenience and reduced renovation needs. These factors underscore the complex interplay of location, amenities, and property characteristics in determining real estate values.

3.2. Model construction

Building on the descriptive analysis, this report leverages R language to delve deeper into the relationship between the logarithmic prices of second-hand houses and various explanatory variables. In order to build the model, we need to define the parameters first.

Table 3. Parameters Definition

Parameters	Definition
Logarithmic Price	Y
Administrative Division	X_1
School	X_2
Subway	X_3
Sea	X_4
Elevator	X_5
Renovation	X_6
Age	X_7
Orientation	X_8
Area	X_9
Random Disturbance	ε

From this we can build model A:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \varepsilon \quad (1)$$

The implementation is carried out in R, with parameter estimation and testing results shown in Table 4. The model's overall F-test is highly significant (P-<0.001), indicating that at least one of the considered factors significantly impacts the logarithmic price. The adjusted R-squared value, R2=0.637, reflects the proportion of variance explained by the model. A closer examination of the t-test results for each explanatory variable reveals the following insights:

Prices per unit area vary significantly across districts, with Dapeng being the lowest and Nanshan the highest, 20.6% higher than Bao'an. Properties with sea views are, on average, 45.2% more expensive than those without. School district properties are 27.3% more expensive than non-school district ones. There's a slight decline in price with increasing property age. Additionally, there's a positive relationship between price and area; larger properties command higher prices. In summary, the value attributed to school district properties varies by region.

Table 4. Model A results.

Variable	Estimate	Std.Error	P	Note
Intercept	1.566	0.045	<0.001	
district Dapeng	-0.794	0.027	<0.001	
district Futian	0.172	0.019	<0.001	
district Guangming	-0.332	0.026	<0.001	
district Longgang	-0.448	0.021	<0.001	Reference group:
district Longhua	-0.115	0.020	<0.001	district Bao'an
district Luohu	-0.139	0.020	<0.001	
district Nanshan	0.206	0.019	<0.001	
district Pingshan	-0.546	0.025	<0.001	
district Yangtian	-0.462	0.027	<0.001	
school	0.273	0.011	<0.001	
subway	-0.014	0.018		
sea	0.452	0.032	<0.001	
elevator	0.052	0.029		
renovation	0.033	0.022		
age New house	0.069	0.023		
age Old house	-0.177	0.015	<0.001	Reference group:
age relatively new house	-0.004	0.014		middle-aged houses
age as older house	-0.024	0.015		
orientation	0.009	0.010		
area	0.001	0	<0.001	
Model Global Tests	P-value<0.001		Adjusted R2	0.63

The advantage of Model A is that because it is a multi-factor model, it integrates multiple single factors under the same model framework for comparison, and it can be simple and fast to analyze the discrete variables under the regression analysis framework, but the disadvantage is also too simple, the interaction between different factors is not taken into account, and the expansion is too poor, so a new model is established with the interaction of the two factors of administrative districts and the school and Model B is established:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \gamma X_1 * X_2 + \varepsilon \quad (2)$$

The results for Model B, as displayed in Table 5, emphasize the interaction between administrative division and school district availability. Initially, this model is compared with the model from Table 4, which lacks the interaction term "Administrative Division * School District Availability," using variance analysis. The highly significant F-test (Table 6) indicates the presence of this interaction effect. This finding suggests that the impact of being in a school district varies across different administrative divisions. For instance, in the Bao'an district, being in a school district can raise the property price by about 55.3% compared to properties not in a school district, which is a substantial increase. Given that Bao'an has few school district properties, the interaction between "Administrative Division" and

"School District Availability" significantly influences property prices. Even in districts like Futian and Nanshan, where there are more school district properties, the presence of a school still offers a positive price uplift. It's important to note that the negative interaction coefficients for Futian and Nanshan do not imply a negative effect on school district properties in these areas but rather indicate that the effect is not as pronounced as in Bao'an.

Table 5. Model B results.

Variable	Estimate	Std.Error	P	Note
Intercept	1.586	0.045	<0.001	
district Dapeng	-0.789	0.027	<0.001	
district Futian	0.184	0.021	<0.001	
district Guangming	-0.293	0.027	<0.001	
district Longgang	-0.493	0.025	<0.001	Reference group: district Bao'an
district Longhua	-0.156	0.021	<0.001	
district Luohu	-0.156	0.021	<0.001	
district Nanshan	0.234	0.021	<0.001	
district Pingshan	-0.537	0.025	<0.001	
district Yantian	-0.292	0.037	<0.001	
school	0.553	0.125	<0.001	
subway	-0.003	0.017	0.859	
sea	0.449	0.032	<0.001	
elevator	0.029	0.029	0.318	
renovation	0.020	0.021	0.349	
age New house	0.065	0.023	0.005	
age Old house	-0.161	0.015	<0.001	Reference group: age middle-aged houses
age relatively new house	0.008	0.014	0.538	
age as older house	-0.009	0.015	0.531	
orientation	0.010	0.010	0.302	
area	0.001	0	<0.001	
district Dapeng*school	-0.139	0.148	0.345	
district Futian*school	-0.309	0.128	0.016	
district Guangming*school	-0.483	0.134	<0.001	
district Longgang*school	-0.167	0.130	0.198	Reference group: district Bao'an*school
district Longhua*school	-0.079	0.130	0.545	
district Longhu*school	-0.192	0.131	0.143	
district Nanshan*school	-0.346	0.128	0.007	
district Pingshan*school	-0.243	0.137	0.075	
district Yantian*school	-0.498	0.131	<0.001	
Model Global Tests	P-value<0.001		Adjusted R2	0.643

Table 6. Model Comparison.

Model	Res.Df	RSS	Df	Pr(>F)
A	2979	193.16		
B	2970	185.86	9	<0.001

3.3. *Discussion*

As can be seen from the results of Model B, its advantage lies in its additivity, which allows it to interact with multiple factors to improve the accuracy of the model prediction, but this is also its disadvantage because it is too additive, which will greatly increase the complexity of the model if it analyzes the interaction of too many factors at the same time. Moreover, for the degree of influence of the interaction,

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a rigorous statistical model is needed to test it, which also requires more workload. But overall, Model B is still the basic direction of the optimal model.

This model has a wide range of applications. It can assist decision-makers in understanding the mechanisms behind property pricing and enable investors to identify potential investment opportunities. Primarily, the model serves as a valuable tool for facilitating second-hand housing transactions. For illustrative purposes, let's use R language and Model B for a simple simulation.

Consider a worker looking to purchase a relatively older home in the Nanshan district. The desired property faces south, aligning with future educational needs. Thus, being in a school district near a subway station is essential. The property should have an elevator, and be fully renovated to save on time and costs. A sea view is not a requirement for this buyer.

Based on these parameters, this paper estimates the property's price per square meter to be approximately 91,300 CNY, making the total price around 8,216,000 CNY. This example showcases how the model can be applied in real-world scenarios to predict property prices based on a set of defined factors, providing valuable insights for potential buyers and investors.

4. Conclusion

This report utilizes the logarithmic price per unit area of second-hand houses as the dependent variable, crafting an array of indicators to characterize second-hand housing features. These variables include administrative division, school district availability, sea view availability, house orientation, housing area, house age, proximity to the subway, elevator availability, and renovation status, totaling 9 independent variables. In addition, Model A and Model B were established to analyze the relationship between factors and house prices, to summarize the advantages and disadvantages of each of the two models, and to draw conclusions. The key conclusions of the report are summarized as follows:

Administrative division, school district availability, sea view availability, house age, and the housing area, show a significant correlation with the logarithmic price per unit area. In contrast, proximity to the subway, renovation status, elevator availability, and house orientation are not as significant. In the Bao'an district, properties within school districts command higher prices, highlighting the potential for personalized property price assessment products. Given the complexity of factors influencing property prices, future research could incorporate additional elements, such as the proximity to top-tier hospitals or supermarkets. Expanding the study to include all districts in Shenzhen could also yield different insights. This analysis not only aids in understanding the current market dynamics but also paves the way for more nuanced and tailored approaches to property valuation in the realm of second-hand housing.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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