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Housing Prices and the Characteristics of Nearby Green Space: Does Landscape Pattern Index Matter? Evidence from Metropolitan Area

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Abstract: This study aimed to examine the association between housing prices and green space characteristics with a special focus on exploring the effects of the shape pattern index. The research was based on a hedonic price model across two main distance buffers from residential properties to urban green spaces. Green spaces were characterized by size and shape measured by a landscape shape index (LSI). This study was based on 16,222 housing transaction data obtained from the website of real estate agencies during December 2019 in the Metropolitan Area of Beijing. Linear regression and semi-log regression analysis were used to examine the associations between independent housing and neighborhood characteristic variables and housing prices. The results suggested that a one-unit increase in the natural logarithm of the landscape shape index (LSI) can increase housing prices by 4% (5543 CNY ≈ 826 USD). Such marginal effects were more pronounced for residences located close to urban green spaces and tended to decay as the distance from residences to green spaces increased. Additional analysis captured the marginal effects of the natural logarithm of the landscape shape index (LSI > 1.3) on achieving the maximum monetary evaluation of the property. The findings of this study suggest that the effects of specific green space characteristics on housing prices should be taken into account in landscape and urban design.

Keywords: green space; shape pattern index; landscape shape index (LSI); hedonic price model; housing price; distance decay effect

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1. Introduction

The value of urban green space is well established not only in moderating urban heat island effects [1,2], improving air quality [3,4], promoting people's mental health and self-rated health [5–7], wellbeing [8–10], and also in contributing to housing prices [11,12]. The influence of parks on house prices has long been recognized. In the 1850s, the New York City Council argued that the creation of Central Park would increase nearby property prices [13]. More recent empirical studies have pointed out that residential proximity to green spaces as well as parks has positive impacts on housing prices across the world. In the UK for example, residents have the willingness to pay an extra premium to live close to urban parks [14]. Similar results have been found in Finland, where residents were found to be willing to pay 4.9 percent more to reside adjacent to natural greenness [15]. Studies in China have reported equivalent results to western countries: in Guangzhou, Jim and Chen [11] found that residential proximity to water bodies and the visibility of green spaces had positive influences on housing prices.

Later studies have focused on how the characteristics of a green space can influence house prices. Clearly, the nature of the green space is a factor in the desirability of a neighborhood. There are all sorts of green spaces, including parks that are open to the public, private golf courses, gardens, and recreational facilities. Not all of these have an equivalent positive influence on house prices. Large, flat, open spaces which are used primarily for sports activities are much less preferred than natural areas that encompass water features [16]. Some green spaces will be of such poor quality, for example, in terms of standard of upkeep, that they may create negative impacts on local house prices [13]. The size and shape of the green space are also likely to impact nearby house prices. While the role of size is arguably straightforward, the influence of shape is less obviously defined. An irregular shape could be seen as contributing to a more distinctive neighborhood, and hence to higher house prices.

Evidence on the role of the shape and size of green spaces on the housing market is limited and mixed. One underlying mechanism is that landscape shape and size are correlated with land use types and patterns that have significant changes, along with the urbanization processes of the metropolitan area in China [17,18]. The continuous changes in land use patterns play a substantial role in influencing the housing price [19]. Several studies have found that the size of a green space had a positive influence on housing prices [20–22]. However, one study found no significant association between park size and housing price, and indicated that smaller parks distributed equally across the urban area might contribute better to housing prices compared to larger parks [12]. This issue of the macro-pattern of green spaces within cities has also been considered by other studies. Xiao, et al. [23] evaluated the effects of different types of green spaces on housing prices. They found that a one-unit increase in a residential development's ratio of green to the total area would lead to an increase of 8.7 percent in housing prices in Shanghai. Similarly, Jiao and Liu [24] quantified that city-level parks had significant influences on amenity values, while district-level parks did not.

In addition to the general effect of residential proximity on the housing premium, some studies have applied more complex measures of accessibility than simple Euclidean distance. Park, et al. [25] undertook a study of the impact of a park in Seoul, taking into account the shortest walking distance while considering crossroads and park entrances. Property values more generally were found to incrementally increase with residential proximity to urban green spaces at specific distance intervals. Crompton [13] reviewed studies of the effects of residential proximity to parks and open spaces on housing value and found that they contribute to housing prices differentially through distance buffers. Specifically, these studies found that the effects on house price of adjacency to a park and open space tend to decay at different rates within and beyond a 500-foot distance buffer. In another recent study exploring the effects of urban green space on housing values in Germany [26], researchers found that the influence of urban parks on housing prices increased with closeness through buffers. For instance, a one unit increase in the residential distance to parks would lead to a 0.1 percent increase in housing price within a 500 m buffer zone, compared to a 0.19 percent increase in housing price within a 1000 m buffer zone.

Many studies have therefore indicated that accessibility to green space, as discussed above, has played an essential role in affecting housing values. Yet, limited studies have focused on exploring the direct relationship between the size and especially the shape configuration characteristics of urban spaces and housing prices. This paper addressed this vacuum by assessing the role of the size and shape of green spaces on housing prices in urban Beijing. In particular, its premise was that irregular large green spaces have a positive impact on house prices. To assess this influence, the paper adopted the use of a shape index developed by ecological studies. Such studies have applied a shape index to green spaces to examine the relationship between fragmentation characteristics and species richness [27,28].

To address this task, the paper applied a hedonic price model. The hedonic price approach has been the conventional method for exploring the association between housing characteristics and value, which can be directly estimated as the marginal willingness to pay for an additional attribute of each property [29,30]. Hedonic models enable the impact of housing structural characteristics, locational/accessibility relationships, and neighborhood and environmental features on housing prices to be quantified [11,23]. The associations between different characteristics and housing prices can be complex and diverse. For housing structural characteristics, traditional studies have found a significant association between housing age, size, storey, number of bedrooms and bathrooms, window orientation, elevators, and housing prices [11,31–33]. Neighborhood characteristics can encompass the accessibility to the nearest social amenities (e.g., schools), train stations, central business districts, and natural landscapes (e.g., parks, forests, urban green space).

Building on the above, we therefore applied a hedonic housing price model that encompassed housing attributes and neighborhood characteristics including green space features. This study provides new insights into examining the impact of specific landscape patterns on the housing market, which reflects the potential correlations between changing land use patterns attributed to urbanization processes and housing prices. This study assessed the effects of specific green space configurations (size and landscape shape index) on housing prices in selected districts of the city of Beijing. The specific aims of this study were to: (1) explore the overall relationship between housing attributes, neighborhood characteristics and green space characteristics and housing price; (2) examine residents' willingness to pay for green space characteristics, notably in terms of its size, proximity level, and its green space shape (using a landscape shape index); abd (3) assess whether residents' willingness to pay for green space characteristics vary incrementally with distance buffers.

The remainder of this paper is organized as follows: Section 2 outlines the materials and methodology. Results are outlined in Section 3. Sections 4 and 5 report the discussions and conclusion.

2. Materials and Methods

2.1. Study Area

The scope of this study was primarily focused on selected urban districts of Beijing, namely Xicheng, Dongcheng, Haidian, Chaoyang, Fengtai and Shijingshan. The distribution of green spaces and the boundary of selected districts are illustrated in Figure 1. It is worth noting that the municipal government of Beijing has massively invested in urban greenness infrastructure in order to provide a better quality of life and potential economic benefits for residents. In total, 31 parks and 13 urban forests were added in 2019, contributing to an 83% coverage rate of parks within a radius of 500 m from residences according to the Beijing Gardening and Greening Bureau (Xinhua, 2019). The 13th Five-Year Plan (Bureau, 2020) expects the coverage rate of green space and parks within 500-m of residences to reach 48.5% and 85%, respectively. A total of 700 hectares of new urban green space, 41 new leisure parks, 13 urban forests and 50 pocket parks are planned to be built in 2020. These policies that continue to expand urban greenness provide a potential underlying pathway for raising the nearby housing premium.

2.2. Housing Data Acquisition

The housing data used in this study were captured from the website of a real estate agency (https://bj.lianjia.com (accessed on 28 December 2019)). Real estate agencies provide access to accurate housing prices at the household level [34]. We captured a list of housing sales prices and structural variables through December 2019 from Lianjia.com by conducting the web-crawling Python program. The original data on residential properties were first accessed by the request methods in the Beautifulsoup library which refers to a Python library for extracting data out of HTML and XML files (https://beautiful-soup-4.readthedocs.io/en/latest (accessed on 2 January 2020)). The data were extracted by selecting a useful keyword stored within the DataFrame format of the Pandas library. Housing price was captured in CNY per square meter per dwelling. Lianjia is one of the largest real estate agents in urban China, with a 50 percent market share in Beijing, providing relatively precise housing information [35]. Housing variables related to structural characteristics were captured, including housing age, housing asking price, the age of the properties, number of bedrooms, number of bathrooms, size of the property, whether the properties have an elevator, the number of storeys in the properties, and window orientation. These are equivalent to previous studies [36].

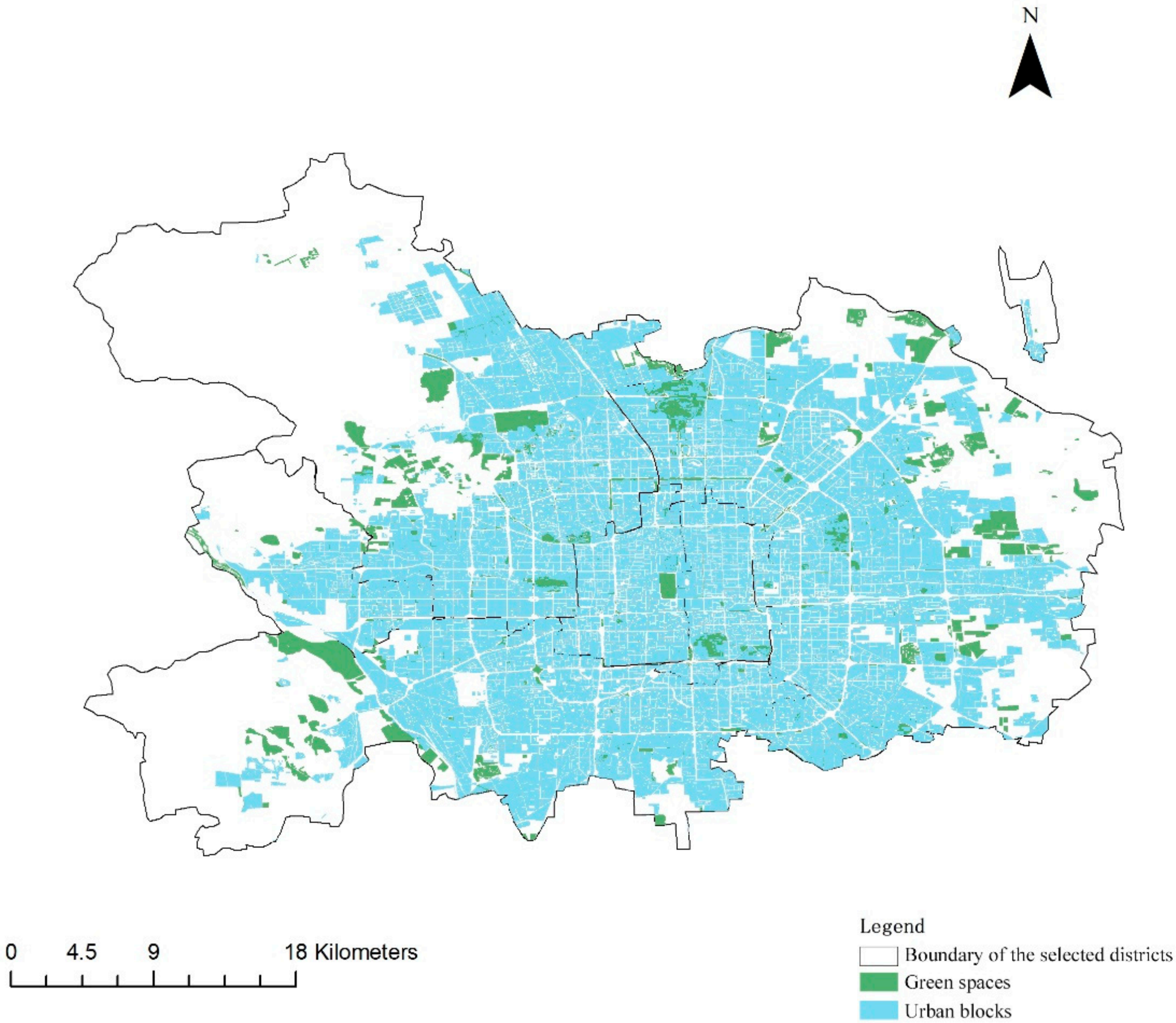

Figure 1. Displays the distribution of boundary of selected districts, green spaces, and urban blocks in Beijing.

Additionally, we captured the coordinates of the latitude and longitude of each property in Baidu Map API (Baidu Developer: https://lbsyun.baidu.com (accessed on 2 January 2020)) and transformed them into WGS-84 coordinates in GIS. To ensure the consistency of housing structures in the study, we excluded properties that were not normal commodity housing, such as villas, loft apartments and Soho apartments. After these exclusions, 16,222 asking price transaction records were included in this study.

2.3. Data on Green Space and Neighbourhood Characteristics

The green space data were obtained from Beijing City Lab (http://www.beijingcitylab.com (accessed on 2 January 2020)), which shared information on 16,721 urban green lands in 287 Chinese cities in 2017 [37]. We narrowed down the scope of the data and selected

1542 green space polygons within the Beijing administrative boundary (see Figure 1). The data included the size of the green spaces while a 'landscape shape index' (hereafter LSI) was calculated for each polygon based on the approach [38,39]. The concept of shape index was first proposed as a diversity index by [39] to quantify habitat edges for wildlife species. LSI has been frequently undertaken to identify the divergence of the shape of a landscape patch from the ideal circle [39,40].

The use of this index is the key contribution of this paper towards understanding the spatial pattern of house prices. In this study, we applied the LSI as a landscape metric to examine the effect of shape configuration characteristics of green space patches on any housing premium. The LSI quantifies the shape of the green space by taking the total length of the green space divided by the total area and adjusting by a constant for a square standard. The equation of LSI can be written as follows:

$$\mathrm{LSI} = \frac{P}{\sqrt[2]{\pi \times A}} \tag{1}$$

where P refers to the perimeter of the patches. A refers to the total landscape area (m^2). If the landscape shape refers to a square, then the LSI equals 1. The larger the LSI, the greater the complexity of the landscape shape. While LSI values are not associated with definitive shapes, higher values suggest more attractive intricate landscapes. Figure 2 displays the shape series with increasing LSI values. All shapes are derived from the green spaces' polygon database.

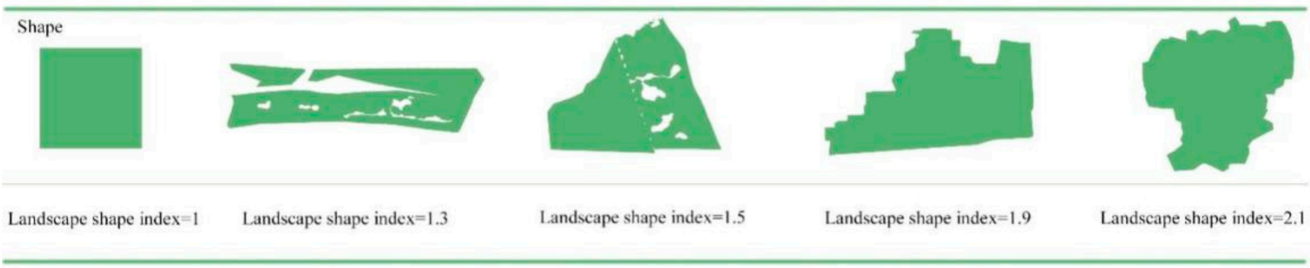

Figure 2. Landscape shapes with increasing LSI value.

To examine whether the marginal effects of LSI on housing prices would decay as the distance from residences to green spaces increased, we defined two key buffer variables. Accessibility to green space from residences was considered in terms of intervals, within 300 m and from 300 m up to 1000 m, as studies have found that these are walkable thresholds for residents' access to natural greenness [41]. We calculated the distance buffers based on residents' home addresses. Two main buffers were therefore generated for access to the nearest green spaces. The definition of the intervals is illustrated in Figure 3.

Regarding the neighborhood characteristics, we used the spatial 'Near' tool in ArcGIS to calculate the direct distance from each property to the nearest green space. We also measured the direct distance to the nearest central business district (CBD) and the nearest subway station that may potentially contribute to the housing premium.

2.4. Construction of the Hedonic Pricing Model

Two functional forms of the hedonic pricing model were employed to assess the associations between housing price per square meter and the accessibility of the green space and its size and shape (LSI), namely, the linear regression [42] and semi-log regression [43,44]. Accordingly, it is not only feasible to interpret the implicit property value [45] but also to identify the percentage of change in the property value. Semi-logarithmic forms have been frequently formulated in hedonic models [46]. In this study, when the association was assumed linear, the equation can be written as Equation (2):

$$\mathrm{P} = \alpha_0 + H\beta + G\mu + N\chi + \varepsilon \tag{2}$$

where P denotes the asking price at the residential unit level. H denotes the matrix of housing structure characteristics. G denotes green space characteristics including our main interest landscape shape index that it is measured in the Natural logarithm form. N denotes the neighborhood characteristics. α, β, μ, χ are associated parameter vectors. ε is a vector of random error terms. When the association was assumed semi-log, the model was specified by a natural log transformation of the housing price and the equation can be presented as Equation (3):

$$\mathrm{LnP} = \alpha_0 + H\beta + G\mu + N\chi + \varepsilon \quad (3)$$

In accordance with the study [47], we separated our model into two main categories. One set of the model included direct distance and the other one included the distance buffer. Both the distance metric and distance buffer were treated as proxies for the accessibility of green space [48]. The rationale behind this was that if the residence is located at a close distance to a specific green space, it might also be located within a closed-distance buffer of a green space [49].

Figure 3. The definition of distance buffers with green spaces around the residences.

3. Results

3.1. Descriptive Analysis

Table 1 presents the descriptive characteristics of the sample (n = 16,222). The average mean of the housing asking price is 80,249.6 CNY (≈11,957.2 USD) per square meter. Generally, the housing price decays with the distance from the central business district. The housing prices of Dongcheng and Xicheng districts, which are closest to the city center, have the highest average prices among the districts, with 113,592.9 CNY (≈16,925.3 USD) and 97,468.2 CNY (≈14,522.8 USD) per square meter, respectively. These are followed by Haidian and Chaoyang districts, with 84,605.3 CNY (≈12,606.2 USD) and 66,710.4 CNY (≈9939.8 USD) per square meter, respectively.

Table 1. Statistical description.

Variables	Description	n	Mean	SD
Dependent variable				
Price	Selling price per square meter in CNY	16,222	80,249.60	28,219.83
Ln price	Logarithmic form of the selling price in 10,000 CNY (Chinese currency, US $1 = 6.9 CNY)	16,222	11.23	0.35
Price in districts				
Price in Shijingshan district	Selling price per square meters in CNY	1862	52,854.39	11,997.59
Price in Fengtai district	Selling price per square meters in CNY	2985	57,166.82	11,324.8
Price in Chaoyang district	Selling price per square meters in CNY	2912	66,710.38	16,588.28
Price in Haidian district	Selling price per square meters in CNY	2672	84,605.26	19,498.39
Price in Xicheng district	Selling price per square meters in CNY	2815	97,468.18	18,376.97
Price in Dongcheng district	Selling price per square meters in CNY	2976	113,592.9	24,492.97
Housing characteristics				
Housing age	2019 minus the construction date of the properties	16,222	26.52	38.04
Bedroom	Number of bedrooms	16,222	2.24	0.82
Bathroom	Number of bathrooms	16,222	1.28	0.55
Housing size	The average size of the property (m^2)	16,222	92.25	47.26
Elevator	Dummy variable, 1 if the property has an elevator	16,222	0.63	0.48
Storey	Category variable: 0 equals to basement 1 equals to the bottom storey (below the 3rd floor) 2 equals to the low storey (between the 4th and 6th floor) 3 equals to the middle storey (between the 7th and 10th floor) 4 equals to the high storey (between the 10th and 17th floor) 5 equals to the top storey (higher than the 18th floor)	16,222	3.05	1.19
Window orientation	Dummy variable, 1 if the residence has north-south facing windows	16,222	0.38	0.49
District	Category variable: 1 represents the Shijingshan district 2 represents the Fengtai district 3 represents the Chaoyang district 4 represents the Haidian district 5 represents the Dongcheng district 6 represents the Xicheng district	16,222	3.65	1.65
Neighbourhood characteristics				
Distance to the nearest green space	Road distance to nearest green space (m)	16,222	564.58	425.19
Distance to subway	Road distance to the nearest subway station (m)	16,222	5302.78	3015.51
Distance to CBD	Road distance to the central business district (m)	16,222	12,217.69	7829.55
Green space characteristics				
Natural logarithm of landscape shape index	The total length of the green space divided by the total area, adjusted by a constant for a square standard	16,222	0.7	0.16

Table 1. *Cont.*

Variables	Description	n	Mean	SD
Green spaces' size (ha)	The size of the green space (ha)	16,222	17.51	55.21
Residence buffer (300 m)	Dummy variable, 1 if housing is within 300 m buffers from the nearest green space.	16,222	0.26	0.44
Residence buffer (300–1000 m)	Dummy variable, 1 if housing is within 300–1000 m buffers from the nearest green space.	16,222	0.61	0.49

Regarding the housing characteristics, the average housing age is 27 years, and the average housing size is 92 square meters. Most of the housing comprises two bedrooms and one bathroom. Approximately 63% of the houses have elevators and most of the residences are in the middle storey of buildings, with 38% of residences having north-south facing windows.

In addition, the average size of green spaces and the average distance to the nearest green space are 17.51 ha and 564.58 m, respectively, which is in line with the policy requirement of the Classification Standard of Urban Green Space established by the Minister of Construction. This policy has required that the service ring buffer of green space around residences should be at least 1000 m if the size of green space is between 2 ha and 20 ha. The average natural logarithm of LSI is 0.7, which refers to a raw LSI of 2.0. While 26% of housing is within 300 m of the green space, 61% of homes in the sample lie within a 300–1000 m distance from the green space.

To detect whether there is potential multicollinearity between dependent variables, we applied the variation inflation factor (VIF) diagnostics in Stata version 14 for Windows. The results suggested that all the VIFs were lower than 4.3, confirming that there were no serious collinearity issues in the ordinary least squares regression model [50].

3.2. Baseline Results

In accordance with our aims, Table 2 presents the baseline results by exploring the effects of green space characteristics on housing prices while controlling for housing attributes and neighborhood characteristics in four columns. Results of the estimation for the linear regression model are presented in Column 1 and 2, whereas results of the estimation for the semi-log model are presented in Column 3 and 4. Two measures of direct distance and distance buffers are, respectively, applied in Columns 1 and 3 and Columns 2 and 4.

Before looking at the relationship between green space and house price it is useful to examine the wider housing and neighborhood characteristic coefficients. They indicate that the numbers of bedrooms and bathrooms, the residence's elevator and window orientation are significantly, and as expected, positively associated with housing price. Specifically, in terms of the results from column 2, an additional elevator provided by the housing would lead to an increase in housing price by 5.5% on an average 3249 CNY (≈484 USD). Every additional bedroom and bathroom in a housing unit will lead to a 1% (550 CNY ≈ 82 USD) and 9% (6691 CNY ≈ 997 USD) increase in the housing price. Interestingly, we find that the size and storey of the housing unit have negative effects on housing price. One possible explanation might be that we used the unit price of each housing unit, which is consistent with one study conducted in Korea where cities in Korea have similar highly mixed land uses and densities [51]. Additionally, we find that housing in different districts plays a significant role in influencing housing prices.

Locations in Haidian, Xicheng and Dongcheng districts were positively associated with housing price compared to residents living in Haidian and Fengtai districts. This is logical, since those districts with higher asking prices are located at a relatively close distance to CBD, which potentially promotes the properties' values. Second, we found that residents are willing to pay for better access to green space and CBD, although the implicit price stays at a low level, accounting for 5.0 CNY (≈0.7 USD) and 1.4 CNY (≈0.2 USD), respectively. In addition, we found a negative effect of proximity to the nearest subway station on housing prices.

Table 2. Hedonic price model incorporating green space characteristics.

	(1)	(2)	(3)	(4)
	Price	Price	Lnprice	Lnprice
Age	5.521	5.105	0.000	0.000
	(3.556)	(3.560)	(0.000)	(0.000)
Bedroom	497.053 **	550.176 **	0.006 **	0.007 **
	(241.492)	(241.627)	(0.003)	(0.003)
Bathroom	6649.785 ***	6691.339 ***	0.086 ***	0.087 ***
	(419.859)	(420.137)	(0.005)	(0.005)
Housing size	−64.680 ***	−65.344 ***	−0.001 ***	−0.001 ***
	(6.016)	(6.025)	(0.000)	(0.000)
Elevator	3285.481 ***	3249.162 ***	0.056 ***	0.055 ***
	(328.368)	(328.635)	(0.004)	(0.004)
Storey	−369.724 ***	−373.778 ***	−0.005 ***	−0.005 ***
	(111.162)	(111.239)	(0.001)	(0.001)
Window orientation	3792.511 ***	3783.455 ***	0.047 ***	0.046 ***
	(304.740)	(304.974)	(0.004)	(0.004)
Shijingshan district	Reference	Reference	Reference	Reference
Fengtai district	−8755.901 ***	−9198.544 ***	−0.109 ***	−0.116 ***
	(611.329)	(611.727)	(0.007)	(0.007)
Chaoyang district	−12,938.66 ***	−13,733.41 ***	−0.156 ***	−0.167 ***
	(825.808)	(824.292)	(0.010)	(0.010)
Hadian district	22,216.37 ***	21,572.51 ***	0.327 ***	0.318 ***
	(565.583)	(565.449)	(0.007)	(0.007)
Dongcheng district	13,629.11 ***	12,507.49 ***	0.171 ***	0.156 ***
	(914.015)	(913.559)	(0.011)	(0.011)
Xicheng district	41,865.95 ***	41,302.11 ***	0.487 ***	0.479 ***
	(710.261)	(708.980)	(0.008)	(0.008)
Distance to green spaces	−5.004 ***		−0.000 ***	
	(0.315)		(0.000)	
Distance to subway	1.111 ***	1.115 ***	0.000 ***	0.000 ***
	(0.057)	(0.057)	(0.000)	(0.000)
Distance to CBD	−1.351 ***	−1.396 ***	−0.000 ***	−0.000 ***
	(0.034)	(0.034)	(0.000)	(0.000)
Natural logarithm of landscape shape index	5439.223 ***	5543.887 ***	0.040 ***	0.041 ***
	(829.323)	(830.391)	(0.010)	(0.010)
Green spaces' size	18.411 ***	17.363 ***	0.000 ***	0.000 ***
	(2.443)	(2.443)	(0.000)	(0.000)
Distance buffer (0–300 m)		7052.248 ***		0.088 ***
		(462.638)		(0.005)
Distance buffer (300–1000 m)		5068.837 ***		0.062 ***
		(416.700)		(0.005)
_cons	73,614.84 ***	66,869.96 ***	11.193 ***	11.109 ***
	(1172.639)	(1247.787)	(0.014)	(0.015)
N	16,222	16,222	16,222	16,222
AIC	361,486.8	361,508	−6927.924	−6870.389
BIC	361,625.3	361,654.2	−6789.429	−6724.201

Notes: Standard errors in parentheses ** $p < 0.05$, *** $p < 0.01$. AIC: Akaike information criterion; BIC: Bayesian information criterion.

Third, as expected, all green space characteristics were statistically significant at the 1% level and the direction of the impact was consistent with our expectations. Among these variables, every one-unit increase in the natural logarithm of LSI can increase house value by 4% 5544 CNY (≈826 USD) on average, which indicates that an improvement in LSI can significantly increase the nearby housing price. When the size of the green space increased by 1 ha, the relative housing price increased by 17 CNY (≈2.5 USD). Two distance buffers from the residence to the green space were positively associated with housing prices. In particular, a one percent increase of green space in 300 m and a 300–1000 m buffer would lead to an increase in housing prices of 9% (3217 CNY ≈ 479 USD) and 6% (2589 CNY ≈ 386 USD)m respectively. This finding is largely aligned with one case study conducted in Beijing suggesting that a 0.5% to 14.1% increase would be observed with respect to housing located 850–1604 m away from green spaces [52].

3.3. Comparison between Two Key Distance Buffers from Residential Property to Green Spaces

In the baseline model, housing price decays with the increasing distance from green spaces. In this subsection, we therefore further explored whether the effects of green space characteristics on housing prices will vary depending on different distance buffers from green spaces. The results from Table 3 are presented in four columns. Columns 1 and 2 present the results by conducting the linear regression model. Columns 3 and 4 report the results by using the semi-log regression model. Notably, Column 1 and Column 3 examine the associations between housing characteristics, green space characteristics, neighborhood characteristics and housing prices within 300 m distance buffers from residential property to green spaces whereas Column 2 and Column 4 explore such associations within 300–1000 m distance buffers from residential property to green spaces.

Table 3. Hedonic price model with different distance intervals from residence to green spaces.

	(1)	(2)	(3)	(4)
	<300 M	300–1000 M	<300 M	300–1000 M
Age	91.027 ***	2.306	0.001 ***	0.000
	(24.954)	(3.609)	(0.000)	(0.000)
Bedroom	−1433.49 ***	1568.546 ***	−0.015 ***	0.019 ***
	(438.593)	(319.400)	(0.005)	(0.004)
Bathroom	5982.370 ***	7186.522 ***	0.074 ***	0.094 ***
	(778.738)	(542.004)	(0.009)	(0.006)
Housing size	−23.694 **	−94.286 ***	−0.000 ***	−0.001 ***
	(10.273)	(8.157)	(0.000)	(0.000)
Elevator	4956.562 ***	3153.681 ***	0.067 ***	0.056 ***
	(644.594)	(425.682)	(0.008)	(0.005)
Storey	−418.954 **	−388.525 ***	−0.005 **	−0.006 ***
	(209.835)	(141.001)	(0.002)	(0.002)
Window direction	4152.365 ***	3667.148 ***	0.046 ***	0.047 ***
	(564.949)	(390.587)	(0.007)	(0.005)
Shijingshan district	Reference	Reference	Reference	Reference
Fengtai district	−2059.774 *	−9764.051 ***	−0.016	−0.132 ***
	(1167.804)	(803.446)	(0.014)	(0.009)
Chaoyang district	−963.475	−15,001.25 ***	0.020	−0.200 ***
	(1544.736)	(1054.562)	(0.018)	(0.012)
Haidian district	29,679.8 ***	21,084.81 ***	0.425 ***	0.303 ***
	(1080.593)	(729.712)	(0.013)	(0.009)
Dongcheng district	25,177.31 ***	11,403.26 ***	0.335 ***	0.124 ***
	(1698.578)	(1195.870)	(0.020)	(0.014)
Xicheng district	53,808.15 ***	42,290.27 ***	0.625 ***	0.474 ***
	(1418.500)	(923.819)	(0.017)	(0.011)
Distance to green spaces	−8.365 ***	−3.762 ***	−0.000 ***	−0.000 ***
	(3.017)	(0.893)	(0.000)	(0.000)
Distance to subway	0.642 ***	1.359 ***	0.000 ***	0.000 ***
	(0.111)	(0.070)	(0.000)	(0.000)
Distance to CBD	−0.952 ***	−1.384 ***	−0.000 ***	−0.000 ***
	(0.068)	(0.046)	(0.000)	(0.000)
Natural logarithm of landscape shape index	7130.456 ***	5418.881 ***	0.061 ***	0.044 ***
	(1485.018)	(1063.307)	(0.017)	(0.012)
Green spaces' size (ha)	−8.799 **	28.652 ***	−0.000 ***	0.000 ***
	(4.411)	(3.184)	(0.000)	(0.000)
_cons	60,703.68 ***	72,922.49 ***	11.031 ***	11.200 ***
	(2412.823)	(1637.938)	(0.028)	(0.019)
N	4288.000	9928.000	4288.000	9928.000
AIC	95,320.89	221,208.8	−2062.173	−4322.276
BIC	95,435.43	221,338.5	−1947.629	−4192.62

Notes: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. AIC: Akaike information criterion; BIC: Bayesian information criterion.

Regarding the housing characteristics, we found that housing price decreases by 1.1% (1803 CNY ≈ 267 USD) and 0.1% (485 CNY ≈ 72 USD), respectively, with regard to the elevator and window orientation variables if residents are living within distance buffers changing from 300 m to 300–1000 m. Similarly, we found that housing price decreases by 71 CNY (≈11 USD) in terms of housing size variables within the same distance buffer, though the estimated effects are relatively small. Conversely, housing price increases by 3.4% (2969 CNY ≈ 442 USD) and 2% (1204 CNY ≈ 179 USD), respectively, with respect to the number of bedrooms and bathrooms when residents are living within a distance buffer change from 300 m to 300–1000 m.

The results indicate a mixed pattern in terms of neighborhood characteristics. Consistent with the results from the baseline model, there was a positive effect of residential proximity to green spaces on housing prices within a 300 m distance buffer from green spaces. Such effects became less pronounced in terms of residents living within a 300–1000 m distance buffer from green spaces. Similarly, a positive association between residential proximity to CBD and housing prices was found with regards to residents living within a 300 m distance buffer from a residential property to green spaces. A slight decrease in housing prices was found in terms of residents living within a 300–1000 m distance buffer from a residential property to green spaces. Conversely, residential proximity to the subway station negatively influenced the housing price in terms of residents living within a 300 m distance buffer from a residential property to green spaces. Regarding the green space characteristics, housing price decreased by 1.7% (1711 CNY ≈ 255 USD) in relation to the natural logarithm of LSI if residents were living within a distance buffer ranging from 300 m to 300–1000 m. Additionally, housing price increased by 37 CNY (≈6 USD) with respect to the size of the green spaces when residents were living within the distance buffer ranging from 300 m to 1000 m.

3.4. Further Analysis

It is noteworthy that the results from prior analyses do not take into consideration neighborhood heterogeneity and are only based on the mean impact of the whole sample. Consequently, this section studied the heterogeneity between the natural logarithm of LSI and three variables: distance buffers (0–300 m), distance buffer (300–1000 m), and green spaces' size dummy.

Findings from the first three rows of the first column of Table 4 show that the cross-term coefficient between the natural logarithm of LSI and distance buffer variables is considered positive when the natural logarithm of the LSI value is greater than 1.3, indicating that, in comparison to residences located outside 300 m, the natural logarithm of LSI is more beneficial in promoting residents' housing prices. Such effects become more pronounced when the value of the natural logarithm of LSI increases. Nonetheless, the cross-term coefficient between the natural logarithm of LSI and distance buffer variables is still positive in terms of the value if the natural logarithm of LSI is greater than 1.3, and the marginal effects of the interaction term on housing prices decreased when the buffer range expanded from 300 m to 300–1000 m.

Table 4. Interaction term between distance buffers' dummy, green spaces' size dummy and LSI dummy.

	(1)	**(2)**
Variables		
Natural logarithm of LSI (LSI $\leq$ 1.3) $\times$ Distance buffer (0–300 m)	−2151.502	
	(2039.206)	
Natural logarithm of LSI (1.3 < LSI $\leq$ 2.0) $\times$ Distance buffer (0–300 m)	1921.477 **	
	(808.856)	
Natural logarithm of LSI (2.0 < LSI $\leq$ 2.7) $\times$ Distance buffer (0–300 m)	4316.784 ***	
	(803.343)	

Table 4. *Cont.*

	(1)	(2)
Natural logarithm of LSI (LSI ≤ 1.3) × Distance buffer (300–1000 m)	−3381.739 *	
	(1996.460)	
Natural logarithm of LSI (1.3 < LSI ≤ 2.0) × Distance buffer (300–1000 m)	1417.924 **	
	(602.240)	
Natural logarithm of LSI (2.0 < LSI ≤ 2.7) × Distance buffer (300–1000 m)	3526.776 ***	
	(593.236)	
Natural logarithm of LSI (LSI ≤ 1.3) × Green spaces' size dummy		−1872.362
		(1940.355)
Natural logarithm of LSI (1.3 < LSI ≤ 2.0) × Green spaces' size dummy		1256.991 **
		(501.544)
Natural logarithm of LSI (2.0 < LSI ≤ 2.7) × Green spaces' size dummy		1335.093 **
		(577.166)
_cons	74,392.93 ***	77,146.92 ***
	(1241.136)	(1241.136)
Control	Yes	Yes
N	16,222	16,222
Aic	361,447	361,523
Bic	361,623.9	361,676.8

Notes: Column 1 refers to explore the interaction term between the distance buffers' dummy and LSI dummy. Column 2 refers to explore the interaction term between green spaces' size dummy and LSI dummy. Controls refer to adjustments for housing structure characteristics, green space characteristics and neighbourhood characteristics. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The second column focuses on the interaction influences between the natural logarithm of LSI and green spaces' size buffer. The results indicate that the natural logarithm of LSI is more beneficial to promote residents' housing prices if residential proximity to a larger size of green space compared to those living adjacent to a smaller size of green space. Similarly, the impact becomes more obvious with the increase of the natural logarithm of LSI.

3.5. Robustness Check

The results of the robustness check are reported in Table 5. In accordance with the general distance decay theory [53], we conducted a different scale of distance buffers to examine whether the influence of natural logarithm of LSI on housing prices is robust. We found that the natural logarithm of LSI is positively associated with the nearby housing price across different distance buffers, which is consistent with the findings from our baseline model. The findings are trustworthy as the positive association between the natural logarithm of LSI and housing price is still statistically robust after changing the distance buffers. In addition, four distance buffers from the residence to the green space are statistically significant at the 1% level, and the direction of the impact is consistent with our baseline model.

Table 5. Results of robustness check.

	(1)	(2)	(3)	(4)
	Price	Lnprice	Price	Lnprice
Natural logarithm of Landscape shape index	5620.815 ***	0.043 ***	5271.238 ***	0.038 ***
	(832.312)	(0.010)	(830.445)	(0.010)
Distance buffer (0–500 m)	7008.434 ***	0.106 ***		
	(974.587)	(0.011)		

Table 5. *Cont.*

	(1)	(2)	(3)	(4)
Distance buffer (500–1000 m)	2948.139 ***	0.053 ***		
	(1003.952)	(0.012)		
Distance buffer (0–800 m)			6201.011 ***	0.076 ***
			(425.316)	(0.005)
Distance buffer (800–1500 m)			4882.665 ***	0.061 ***
			6201.011 ***	0.076 ***
Control	Yes	Yes	Yes	Yes
N	16,222	16,222	16,222	16,222
AIC	361,554.9	−6854.140	361,528.1	−6840.925
BIC	361,701.1	−6707.952	361,674.3	−6694.737

Notes: Controls refer to adjustments for housing structure characteristics and neighborhood characteristics. Standard errors in parentheses *** $p < 0.01$. AIC: Akaike information criterion; BIC: Bayesian information criterion.

4. Discussion

This paper explored the association between housing prices and green space characteristics by standardizing for housing/neighborhood characteristics. It also compared the difference in housing prices between distance buffers from residential property to green spaces. The evidence highlights the fact that the impact of the shape of green space (LSI) on housing prices varied across distance buffers and the size of the green spaces. The maximum impact on property value occurred when residential properties are located at a close distance to nearby large green spaces with a higher value for LSI.

4.1. The Effect of Green Space Characteristics on Housing Price

As expected, we found that the size of a green space has a positive impact on housing prices, which aligns with results found in previously in the literature [54]. Moreover, we found a positive effect for residential property prices within a 300 m distance interval from green spaces. The results further indicate that the housing price then decays with the distance from green spaces, which is in line with other findings [26]. The landscape shape index (LSI), which is our key variable, is positively associated with housing prices, at the statistically significant 1% level. Additionally, our finding provides substantial evidence supporting the view that LSI as an independent shape configuration of a green space patch influences residential value. It is clear that a higher LSI would contribute to higher housing prices nearby, and a curved greenness value contributes more than a square one. One possible explanation might be that irregularly shaped boundaries of patches play an important role in creating sustainable and ecologically sound landscape conditions which contribute to housing premiums [55], while beautiful ecological landscapes bring developers great benefits and willingness for ecological protection, thus promoting the rise of housing prices [56]. On the other hand, the services individuals perceived from the green spaces may be split into those that can be identified as direct-use values and those that can be identified as indirect use values. Direct-use values denote benefits individuals can directly obtain from the green space. For example, amenities provided by that green space can attract more people to access green spaces, thereby prompting people to purchase houses nearby [57]. Indirect-use values refer to values provided by green space that sustain ecological landscape conditions through services such as the maintenance of water quality and indigenous biodiversity. Such a potential non-use value might contribute to housing premiums in the long term, which should not be overlooked. Another way to look at this relationship is that, given that plant species richness is associated with a high LSI score [28], so home buyers are willing to pay more for residential units with this experience.

4.2. Further Analysis and Robustness Check

Findings from this analysis demonstrate that different interaction terms between buffers and size and LSI quantify the evidence that the larger the size of the green spaces, the closer properties are to green spaces, the higher a value the property can achieve, whereas our study suggests that the value of the natural logarithm of LSI greater than 1.3 might provide benefits to promote the housing premium. This finding sheds new light on the underlying mechanism that configuration shape index should be taken into account in making policy decisions related to green space preservation and allocation. Planners and designers should comprehensively consider this index when conducting site selections of urban greenness, rather than simply calculating the size of green spaces, or measuring the direct distance to green spaces. In addition, more commercial housing should be encouraged to build in the suburban area instead of the city center, since limited urban green spaces are located in the urban area whereas a large-scale vegetation-dominated landscape is located in the rural area [58]. Results from the robustness check indicate that the positive association between the natural logarithm of LSI and housing price is statistically robust after changing the distance buffers. Specifically, we found that the LSI-housing price association decays as the distance buffer increases. Such a distance-decay effect is largely aligned with one study suggesting that different types of open spaces have implicit marginal price functions that decrease as the distance from the home address to the open space rises [59].

4.3. Contributions and Limitations

Our findings provide empirical evidence of the capitalization of green space shape configuration characteristics in housing prices. This study broadens the horizon of the urban designer and planner and recommends that more attention be paid to the shape and size of green spaces. It also promotes developers' awareness of achieving the potential property-implicit value by providing technical support for the construction of landscape diversity. Based on the big data sample in urban Beijing, this study provides evidence that landscape shape index (LSI) can be used as an independent reference index for landscape and urban planning and can also be applied as a shaped patch in the evaluation of a housing premium. This study will helps urban designers and planners realize that they should focus more on reconsidering the shape configuration of an environmental feature and not just its size, for example, in cities where green spaces are dominated by small patches [60]. Additionally, it is worth noting that the LSI can serve as the reference for megacities with respect to the design standard and distribution of green space resources.

In addition to these contributions, the limitations of this study are threefold. First, it has been suggested that environmental and visual contacts with green space play an essential role in contributing to housing prices [61]. For example, environmental quality [62], air quality [63,64] as well as the noise level of the neighborhood [65] can positively influence the housing price. However, we have not controlled for housing price effects of environmental quality and visual amenities in the potential price function due to data limitations. Second, empirical studies have suggested different types of natural greenness may have different impacts on housing prices [20,66]. However, we do not have the layout of the types of green spaces in our dataset due to data restrictions. These issues warrant further study. Lastly, the spillover effects of the landscape pattern index on housing prices might be overestimated, as we used the offer price instead of the transaction price. Evidence regarding the relationship between the landscape pattern index and transaction prices should be quantified if the transaction data are available. Future studies should shed new light on matching spatial POI data with environmental quality to provide potential information on the economic value of urban green spaces for stockholders.

5. Conclusions

To the best of our knowledge, this is the first study to evaluate the influence of green space shape configuration characteristics on housing prices within the metropolitan area. The overall findings from this study indicate that housing characteristics, neighborhood characteristics and green space characteristics are positively associated with housing prices. These effects are more pronounced for residents living close to urban green spaces and tend to decay as the distance from residences to green spaces increases. The landscape shape index plays a significant role in influencing the spatial pattern of housing prices where a one-unit increase in the natural logarithm of the LSI can increase housing prices by 4% (5543 CNY ≈ 826 USD). The LSI tends to be more sensitive to supporting a housing premium within relatively close distance margins of urban green spaces. These results highlight the importance of considering the direct effect of green space shape configuration on housing prices. It provides potential evidence for stakeholders to consider specific green space characteristics in urban planning and design.

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