Revealing the value of urban parks for nearby residents: a hedonic pricing study in Beijing

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Abstract

Providing amenities for citizens, urban parks play an important role in improving the quality of life for city dwellers by supplying recreation services and mitigating environmental problems. Especially during the COVID-19 period since 2020, the demand for urban parks has been expressed dramatically by the increasing visiting numbers. To investigate to what level urban parks are promoting residents' wellbeing, we assume the value of welfare improved by a nearby park could be reflected in the citizen's willingness to pay for the housing price premium near an urban park. We applied an economic valuation approach (hedonic pricing method) to assess the premium contributed from a nearby park to the housing price relying on an extensive database of residential property transactions for the central urban area of Beijing relating to the past 10 years. After the initial analysis, we found the average housing price would drop 0.44%, or 20, 907 yuan (2,613 euros) when the nearest park located 100 m further away. To control for unobserved heterogeneity, the study area was subdivided into different 750 m large park-zone areas. And found this price premium impact is the strongest and most significant for large urban parks where the premium is 0.75 % or 35,490 yuan (4,436 euros) if the park proximity increases 100 m. This study provided a method for urban planners to better understand resident's valuation for urban parks and could help them to decide the optimal location for an urban park construction and thus the well-being of local residents with a further cost-benefit analysis.

Keywords: urban park, valuation, hedonic pricing, green space

Acknowledgement

It was quite a rich life experience of following this fruitful program from which I learnt and progressed to a big extent regarding my knowledge and understanding in this spatial economic field. I really would like to thank many people who guided me through this difficult COVID-19 studying period. Firstly, I definitely appreciate the supervision and support from my supervisors, Dr. Eric Koomen and Prof. Jan Rouwendal, who gave me so much revision and enhancing suggestions to push forward my research ideas in a more scientific and systematic direction. I would very like to thank the program coordinator Prof. Hans Koster, who responsively organized our study process in which way we could focus on learning and progressing. I would also like to thank the research coordinator Dr. Mark Lijesen's diligent guiding us through the whole systematic research process and training. And many thanks to our secretary Ms. Hedda Werkman who helped me so much in getting access to the study facilities at Vrije Universiteit Amsterdam. I would like to thank all the colleagues who taught me so much precious knowledge and helped me to improve myself during the online courses. Last but not least, I am the most grateful to my families and friends who have been giving me full support to achieve my study and dreams all the time. The knowledge and methods I learnt from this STREEM program would definitely help me in my academic research and career. I hope all the best to all the teachers and classmates I got to know in the last online study year.

1 Introduction

1.1 Research question

Providing amenities for citizens, urban parks play an important role in improving the quality of life for city dwellers by supplying recreation services and mitigating environmental problems. Especially during the COVID-19 period since 2020, the demand for urban parks has been expressed dramatically by the increasing visiting numbers (Cheng et al., 2021). Another reason to pay attention to urban parks is that less urban space is left for parks to supply amenities as construction continues to house more people in cities (Derkzen, 2017).

This increasing demand of urban parks versus the scarcity of supply for them makes it necessary to estimate the value of a park which could be helpful to optimize the land value as well as the city dwellers' welfare when the desire of an urban park is satisfied with the least loss of opportunity cost of other profitable types of land use. On the other hand, this would help fulfil sustainable development goals (SDG) to create more liveable cities where the whole society would go towards a better development direction when the social well-being is satisfied.

Therefore, how to estimate the value of a park is a crucial part in land use planning process. Many studies have been done in order to value these services supplied by urban parks and green spaces with contingent valuation (Brown et al., 2018) or monetary valuation (Dekkers & Koomen, 2013). Among all of these methods, hedonic pricing is the most popular. However, most of related studies were conducted in the housing markets of the EU and the US, less is known about China (Brander & Koetse, 2011). Therefore, in this case study, the author conducted a hedonic pricing method to calculate the average housing price premium in the housing market of central Beijing area.

The research questions are: 1. How much is the average value of an urban parks for a nearby household in central Beijing areas? 2. How this value differs between households in this area?

1.2 Assumption and Hypothesis

Before answering the research questions, we applied one assumption and proposed two hypothesises based the common sense and previous research as following:

Assumption: Urban parks are important to residents' daily life, people benefit from living closer to an urban park, therefore, people would pay higher to live closer to an urban park. This gives: Value of an urban park = Benefits people could derive = Housing price premium.

Hypothesis: 1. Housing price is higher if this house is located close to an urban park within a threshold. 2. The closer the proximity to an urban park, the higher the residents would pay for the house.

1.3 Literature review

As the main goals were to investigate how much value could a household generate from living close to a park in general and how the impact differs between households, a literature review was conducted to understand how an urban park could impact the nearby housing price and how proximity could impact the magnitude of the housing price premium.

Generally speaking, there is a threshold for an urban park to provide its services to a nearby household and the value could be related to the proximity to a household. Furthermore, as many studies mentioned, the heterogeneity between each urban park could have different impact on the housing premium. For instance, the size of the park, the bigger the size is, the opportunity to enjoy more benefit is higher (Poudyal et al., 2009). The type of the park, the quieter type of parks is more attractive to households be adjected to (Crompton, 2001).

In this research, we mainly focused on the first scope, so how the distance from park could impact the social welfare of a household on average. And the heterogeneity of park values caused by their different characteristics will be not be investigated in this research.

To start with, the author would like to introduce some previous research regarding what is the value of urban parks.

1.3.1 Value of urban parks

Urban parks provide city dwellers plenty of benefits in different aspects (Sadeghian & Vardanyan, 2013). The benefits from two representative perspectives were commonly mentioned in literature. One is the eco-environmental benefits, for instance, preserving plant and animal habitat and diversity (Cornelis & Hermy, 2004), improving air quality, mitigating noise, filtrating water, regulating microclimate (Chen & Wong, 2006). The other one is the social-cultural benefits, for instance, providing recreation opportunities, aesthetic views (Godbey & Mowen, 2010; Scholte et al., 2015).

Interestingly, a study from More et al., (1988) classified these benefits into two categories, namely on-site or internal benefits that accrue to visitors directly using parks, and the off-site or external benefits that accrue to those outside parks. Internal benefits are more related to the socio-cultural benefits for visitor while the external benefits are more related to eco-environmental benefits for inhabitants. Residents who live near a park could receive both internal and external benefits. Because they could enjoy a better micro-climate regulated by a park in their neighbourhood while they own the advantage of closer access to a park to consume the internal benefits.

1.3.2 Value of urban parks on housing price

Most of the studies reviewed in this research showed a significant result that the price of a house increases with its access to urban parks and public open spaces. Three types of analysis of the impact of a nearby urban park and green spaces on housing price premium are commonly applied in previous research: The first one is park proximity in term of the actual distance to the nearest park; The second one is applying buffer zones in terms of the distance to the nearest parks; And the last one is the proportion of green space within a certain distance neighbourhood.

Park proximity is one of the most relevant domains regarding the value of an urban park; perceived and actual walkability of the distance to parks are related to both the on-site and external benefits residents could obtain (del Saz Salazar & García Menéndez, 2007). Poudyal et al., (2009) demonstrated the further a house was from a park the lower the housing price was in Roanoke, Virginia. Another study from Morancho, (2003) even found only the distance from a green area was significant among all the environmental variables concerned in Castellón, Spain. A study in Zhejiang, China also showed the proximity to parks had a positive effect to the housing price (Wen et al., 2015). Czembrowski & Kronenberg, (2016) applied the walking distance as the park proximity variable which was more rational compare to the linear distance. However, some research showed a negative impact from an urban park when a house is adjacent to a park due to nuisance factors and a positive impact if the house is located 2-3 blocks away from a park (Crompton & Nicholls, 2020).

The second method is classifying the distance as several buffer zones. Dekkers & Koomen, (2013) analysed the impact of the presence of open spaces in 10-25m, 25-50m, 50-75m, 75-100m on the housing price respectively and found that a significant impact of open spaces on the housing price was within 25m in all regions and 50m in one region. Similarly, Sander & Haight, (2012) used the tree cover percentage within 100m, 250m, 500m, 750m, and 1000m neighbourhood and found tree cover positively influenced the nearby housing prices within 750m.

The third method is the proportion of green spaces. Geoghegan, (2002) analysed the influence of open space percentage in 1600-m buffer on housing prices and found a positive effect. Tyrväinen, (1997) applied the green space percentage as the access for households and found a significant positive correlation between the green space access with the housing price premium.

Other than these methods regarding the value of an urban park, the other issue often mentioned in the literature is the distance threshold at which the park influence on housing premium would diminish to zero, as called a park influential threshold in this study. This number varies among all the studies and generally substantial influence could be up to 150m and even higher in the case of a large park or open space (Crompton & Nicholls, 2020).

Submarket matters. Some studies showed the difference of social-economic demographical context in a specific neighbourhood could impact the residents' preference of urban parks and public open spaces and hence, influence the housing premium. Anderson & West, (2006) pointed out using the average house premium at the metropolitan level could lead to bias of the actual value of green spaces. By comparing the values of green spaces at the overall market level and the submarkets level in Knox County, Tennessee, the United States, another study from Cho et al., (2006) stated that the marginal effect of green spaces on housing price varied widely in each submarkets while the overall impact was much smaller in the whole country level.

Dekkers & Koomen, (2013) also conducted the hedonic valuation of open spaces of three local Dutch housing markets to avoid the bias due to submarkets distinctions and they found different influence of open spaces on housing prices in different submarket. In a literature review study, Crompton & Nicholls, (2020) concluded that more localized other than generalized analysis was needed for a precise valuation of urban parks and public open spaces. In this research, the district fixed effect was applied to solve the submarket heterogeneity problem.

1.3.3 Valuation methods

Up to now, many different methods to quantify the benefits of urban parks and public open green spaces for urban dwellers have been developed (shown in Table 1). Most of them could be classified into two different main categories. One is revealed preference method. For instance, Iamtrakul et al., (2005) applied travel costs method to identify users' benefit from visits to public parks in Japan and the economic value of these parks. This method could provide results which are easy to interpret. However, the count of visits only demonstrates the internal benefits without external benefits. Another common method of revealed preference is hedonic pricing. Dekkers & Koomen, (2013) applied this method to assess the impacts of the availability of different types of open space on house values, which is an efficient way to imply both internal and external benefits of open spaces for nearby residents. Rouwendal et al., (2017) effectively estimated the value of water body in Amsterdam with this method as well.

The other category to assess the value of urban parks and public open spaces is stated preference. For instance, Jim & Chen, (2006) applied contingent valuation by asking participants about their willingness to pay to use urban green spaces and found parks were the most popular green spaces. Brown et al., (2018) used participatory mapping method by asking people to map the sites according to their preferences. More et al., (1988) stated three valuation techniques, namely travel cost, contingent valuation, and hedonic pricing, among which the first two methods are commonly used to value internal experiences while the last one can estimate both internal and external benefits.

Table 1 Overview of methods assessing the benefits from urban parks and public green spaces

Method	Preference studied	Valuation type	Benefits included	Research example
Travel cost/time	Revealed	Monetary	Mostly social-cultural, for instance recreation	Iamtrakul et al., (2005)
Hedonic pricing	Revealed	Monetary	Integrated benefits	Dekkers & Koomen, (2013)
Contingent valuation	Stated	Monetary	Mostly social-cultural	Jim & Chen, (2006)
Participatory mapping	Stated	Social valuation	Mostly social-cultural	Brown et al., (2018); Zhou et al., (2018)
Photograph analysis	Revealed	Social valuation	Mostly social-cultural	Tieskens et al., (2018)
Integrated assessment	Revealed	Social valuation	Integrated benefits	De Ridder et al., (2004)

The focus of these assessment methods varies among social valuation, biological value, and monetary valuation. All of them are efficient approaches to measure the value or preference of the green spaces for human beings. The monetary approach is the most acceptable and understandable for people and it enables the comparison between different objects (Engström & Gren, 2017).

1.3.4 Research goals in this study

As concluded from previous research, urban parks mainly provide eco-environmental and socio-cultural benefits for nearby residents; These benefits of parks and open spaces were commonly quantified by revealed preference and stated preference. And the hedonic pricing method from revealed preference could capture both on-site and external benefits for nearby residents. However, most previous hedonic pricing studies were conducted in housing market within EU or the US, much less hedonic pricing studies were conducted in China, even less applied in the urban park scope.

Therefore, the author conducted a specific research to analyse how park proximity impact the resident's housing price from a nearby urban park in the housing market of Beijing, specifically, how much extra price would a resident pay for a house to live closer to an urban park in this market. This research revealed how urban parks are valued by nearby residents in this market. The results would be helpful for urban planners and policymakers to estimate the value of an urban park in order to improve the total social welfare where the added housing price value is higher than the sum of the opportunity cost of constructing anything else in this location plus the park construction expense.

2 Data and methods

2.1 Case study area

This study was conducted in the central areas within the 5th ring road in Beijing and encompasses (parts of) seven districts, namely Dongcheng, Xicheng, Chaoyang, Fengtai, Haidian, Shijingshan and Daxing. Beijing is the capital and direct-controlled municipality of the People's Republic of China and is divided into 16 administrative districts and 1 Beijing Economic-Technological Development Area. This study focused on the main areas within the 5th ring road (approximately 100 km long) which is the first highway around Beijing city (built from 2000 to 2003) and the boundary between urban and rural areas. The 5th ring road area occupies approximately 660 km^2 which accounts for 4% of the total area of Beijing. It is home to almost 10.5 million people, or about 50% of the total population of Beijing (National Bureau of Statistics, 2014). The general geographical condition of this case study area is shown in the Fig. 1. To gain better understanding of the residents' preference of urban parks in Beijing, 186 parks within the 5th ring road were selected.

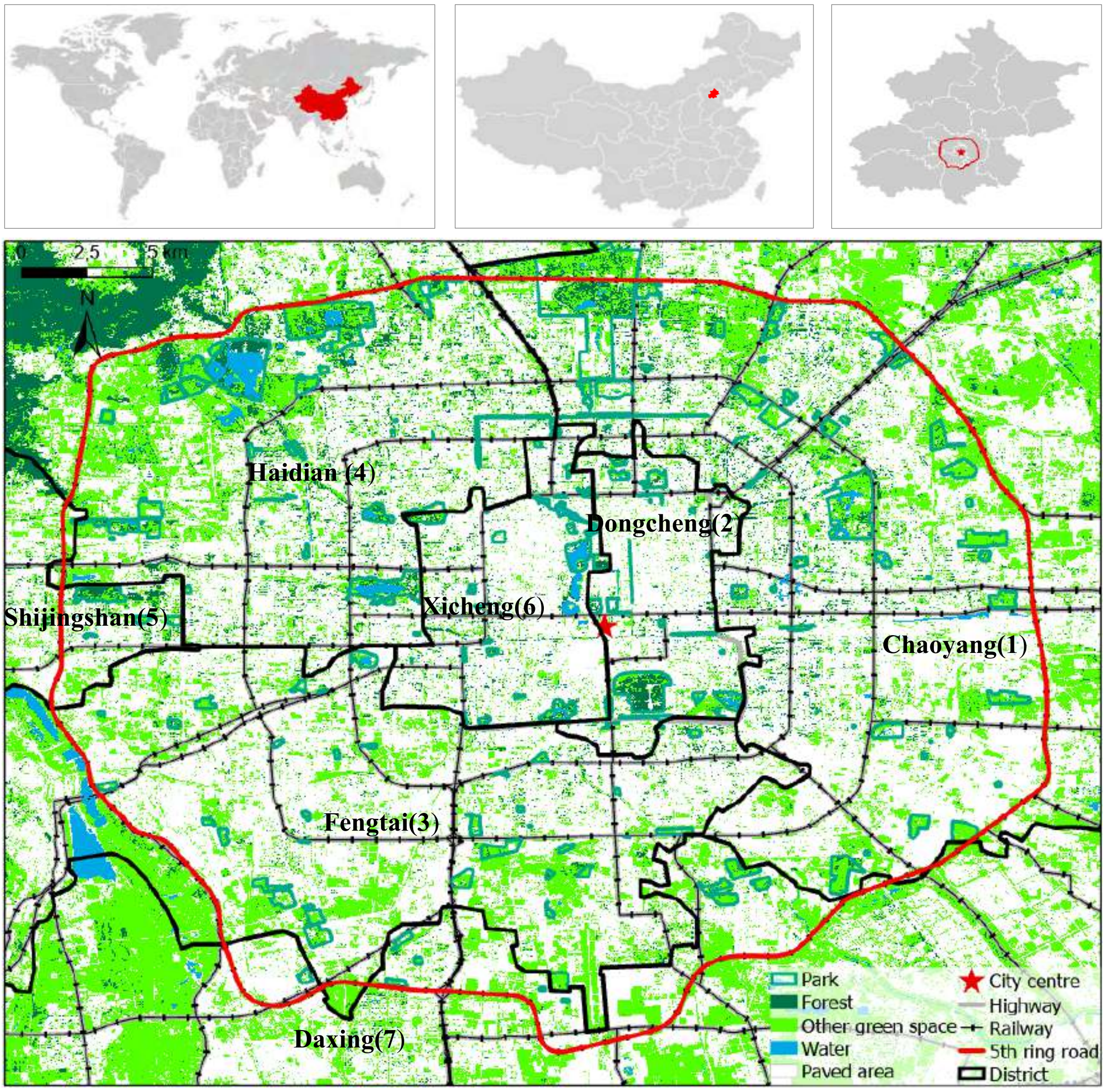


Fig. 1 Case study area, located within the 5th ring road of Beijing

2.2 Data

2.2.1 Data sources

Four datasets listed in Table 2 were applied in this research. In order to delineate park boundaries the author made use of the Beijing digital map which was acquired from Geographical Information Monitoring Cloud Platform data showing green regions of urban parks in Beijing. The second one is housing dataset (2010-2020) generated by web crawling the historical housing transaction records from Lianjia website. The third one is Finer Resolution Observation and Monitoring of Global Land Cover 2017 10-m resolution (FROM-GLC10 2017) dataset from Department of Earth System Services, Tsinghua University. This dataset offers the essential land cover types , for instance, green spaces and water land cover, to derive the neighbourhood green and blue percentage in the study area. The fourth one is the Point of Interest (POI) dataset acquired from Baidu Map API. This dataset provides the spatial coordinates of location characteristics that have value to home owners such as metro stations, highway entrances, shopping centres.

Table 2 Data introductions.

Dataset	Resolution	Time	Variable	Source
Beijing digital map	1:10,000 vector	2015	$Park$	https://map.baidu.com/
Housing dataset	Housing unit	2011-2020	$Price$	https://lianjia.com/
			$YEAR$	
			$Housing$	
			$Property$	
			$Construction$	
FROM-GLC10	10m×10m	2017	$Neighborhood$	https://www.dess.tsinghua.edu.cn/
POI	Point vector	2021	$Location$	https://lbsyun.baidu.com/

2.2.2 Variables applied in this study

Mostly, the variables used in the hedonic pricing models are classified into three main dimensions: First is the bundle of the conventional determinants of housing prices, namely the structural characteristics of houses including size, number of rooms, age, etc.; the second is the bundle of neighbourhood factors, including land use coverage, tree volume, etc.; the third is the location bundle, for instance, proximity to the nearest school, park, metro station, shopping centre, etc. (Morancho, 2003; Sirmans et al., 2005). In this research, the proximity to the nearest park is our variable of interest.

To analyse the impact of the proximity on the value of parks, the most common form of hedonic pricing is semi-log linear which can present the change of housing price in a percentage, to avoid the magnitude problem that the houses with higher prices could get higher effect (Sirmans et al., 2005). Therefore, this method was applied to value the park proximity in a monetary form. The author included different categories of variables that could impact the nearby housing price, namely transaction characteristics, park proximity (variables of interest), structural characteristics, property characteristics, construction characteristics, neighbourhood characteristics, location characteristics, and the district-fixed effect, and the park-fixed effect. A description of all these variables is shown in Table 3. The housing transaction dataset includes 450,525 transaction records during 10 years from 2011 to 2020 (excluding around 300,000 invalid or omitted records). The data cleaning processes are listed in Appendix B.

Table 3 Descriptive statistics of the variables used in this study

Variable	Observation	Mean	Std. Dev.	Min	Max
Transaction characteristics					
Price (¥)	450,525	4,719,436	3,152,915	100,000	80,000,000
Ln(Price) (¥)	450,525	5.994	0.5575524	2.303	8.987
Year (10 dummies: 2011-2020)	450,525	2016.4	2.4	2011	2020
Structural characteristics					
Housing characteristics					
Floor area (m^2)	450,525	81.5	39.0	10	785.9
Ln(floor area)	450,525	4.271	0.384	2.303	6.373
Number of rooms	450,525	5.3	1.4	1	20
House type	450,525	5 types			
Height type	450,525	6 types			
Decoration type	450,525	4 types			
Window direction dummies (0/1)	450,525	8 directions + 1 other			
Property characteristics					
property ownership type	450,525	14 types			
property fee	450,525	2.1	275.4	0	76.5
Construction characteristics					
Pres. of lift (0/1)	450,525	2 types			
lift-house ratio	450,525	0.357	0.181	0.011	20
Building construction year	450,525	1997.1	9.2	1906	2019
Ln(Num. apartment)	450,525	7.245	0.881	1.099	9.473
Spatial characteristics					
Park proximity (m)					
Dist. to the nearest park	450,525	673.5	437.7	0	2,744.7
Dist. to the nearest large park	450,525	1,379.3	8.429.3	0	5,400.5
Dist. to the nearest Class1 park	450,525	1,976.7	1,514.8	0	7,569.2
Dist. to the nearest Class2 park	450,525	1,118.5	767.3	0	4,866.3
Dist. to the nearest Class3 park	450,525	1,582.9	955.8	9.2	5,400.5
Dist. to the nearest Class4 park	450,525	3,564.0	2,334.1	0	14,407.9
Neighbourhood characteristics					
% green and blue in 50m	450,525	0.251	0.224	0	1
% green and blue in 50-200m	450,525	0.215	0.121	0	0.795
Pres. of highway in 300m (0/1)	450,525	2 types			
Pres. of railway in 50m (0/1)	450,525	2 types			
Location characteristics					
Dist. highway entrance (km)	450,525	1.321	0.896	0.018	5.678
Dist. metro station (km)	450,525	0.724	0.434	0.047	3.887
Dist. city centre (km)	450,525	8.406	3.021	0.671	16.817
Dist. shopping centre (km)	450,525	0.674	0.417	0.005	4.586
District-fixed effect	7 districts				
Park-fixed effect	56 park influential radius				

2.2.2.1 Transaction characteristics

One part of transaction characteristics is the housing transaction price and the other is the transaction year. The year of transaction is included as a dummy control variable with respect to the nonlinear coefficient with housing price in the seven districts of Beijing shown in Fig. 2. The observation summary is listed in Table 4. A general time trend regarding the average transaction prices for each of the seven districts during the 10 study years are shown in Fig. 2.

Table 4 Observation summary of 10 years transaction

Year	Freq.	Percent	Year	Freq.	Percent
2011	3,633	0.81	2016	81,007	17.98
2012	26,217	5.82	2017	38,964	8.65
2013	34,483	7.65	2018	53,43	11.86
2014	32,506	7.22	2019	53,169	11.80
2015	70,525	15.65	2020	56,591	12.56
Total				450,525	100

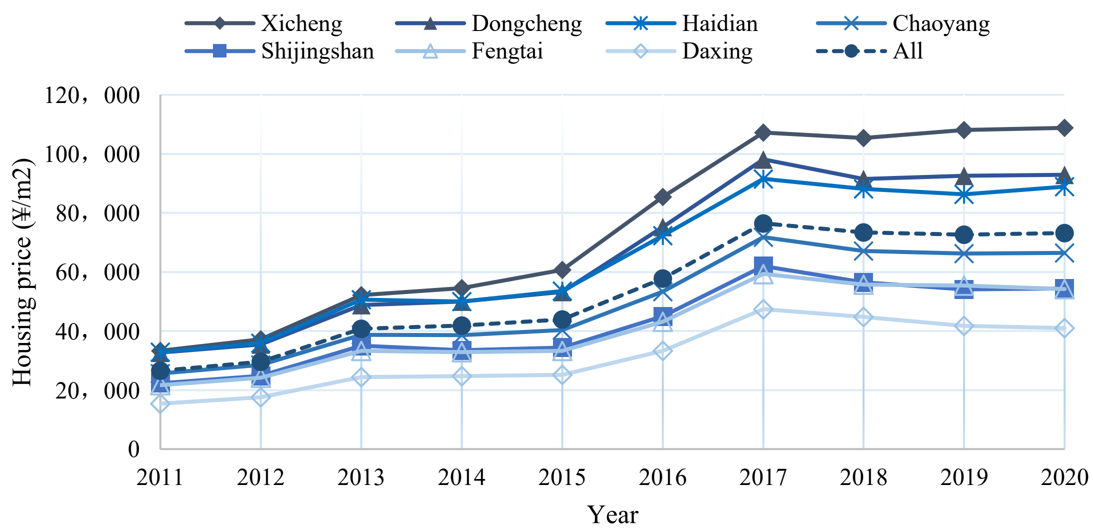


Fig. 2 Average housing price per district during from 2011 to 2020

2.2.2.2 Park proximity

The size of the included parks ranges from 0.1ha to 900 ha. These green spaces without specific park names are not included as urban parks but treated as two neighbourhood environment control variables in this study. According to previous studies regarding classifying different types of parks with different scales (Cheng et al., 2021; Fan et al., 2017; Tu et al., 2020), the author categorised all the parks into four scales, 35 community-scale urban parks (class 1) with an area between 0.1 to 2 ha, assumed as the street corner parks; 96 neighbourhood-scale urban parks (class 2) with an area between 2 and 20 ha, assumed as few facilities inside; 50 district-scale urban parks (class 3) with an area between 20 and 100 ha, assumed with good facilities and management; and 6 city-scale urban parks (class 4) with an area over 100 ha, assumed as well-facilitated famous urban parks. The latter two classes were categorized as the large parks in this study.

2.2.2.3 Housing characteristics

The housing characteristics include floor area (in natural logarithm form), number of rooms, use type, level type, decoration type, and dominant window direction dummies (8 directions: east, northeast, southeast, north, south, west, northwest, southwest, and no window) shown in Table 5.

Table 5 Summary of observation regarding different housing characteristics

Level of house	Freq.	Percent	Window dir.	Freq.	Percent	House type	Freq.	Percent
top	46,464	10.31	East	81,792	18.15	Apartment	449,989	99.88
high	101,248	22.47	Northeast	9,094	2.02	Villa	445	0.10
medium	169,934	37.72	Southeast	23,379	5.19	Courtyard	47	0.01
low	96,514	21.42	North	17,193	3.82	Bungalow	23	0.01
bottom	33,944	7.53	South	256,261	56.88	Service Apart.	21	0.00
basement	1,555	0.35	West	32,39	7.19	Total	450,525	100
unknown	866	0.19	Northwest	8,61	1.91	Decoration	Freq.	Percent
			Southwest	21,564	4.79	Rough	6,398	1.42
			None	242	0.05	Simple	138,387	30.72
						Deluxe	179,574	39.86
						Other	126,166	28.00
Total	450,525	100	Total	450,525	100	Total	450,525	100

2.2.2.4 Property characteristics

Two important property characteristics were adopted in this study. One is ownership right type in order to control the housing price affected by ownership right policies in Beijing. The other one is the property service fee applied to control the community related impact on housing price. As the property services fee is the same for households located in the same community and it could reflect the community quality in a certain level. Its impact on housing price might be added into the impact from the proximity to an urban park if we do not consider this variable. Table 6 lists .

Table 6 Summary of observation regarding different ownerships right variable

Ownership right type (id)	Freq.	Percent
class I economically affordable housing (1)	2,129	0.47
village housing (2)	1	0.00
class II economically affordable housing (3)	4,796	1.06
using right (4)	8	0.00
public rental housing (5)	241	0.05
military estates (6)	5	0.00
commercial housing (7)	406,947	90.33
central government housing (8)	5,563	1.23
orientation placement housing (9)	23	0.01
purchased housing(10)	26,728	5.93
school housing (11)	4	0.00
personal housing (12)	3,591	0.80
self-built housing (13)	1	0.00
low-cost commercial residential housing (14)	488	0.11
Total	450,525	100

2.2.2.5 Construction characteristics

Four types of construction characteristics are applied in this stay. These are the presence of a lift, life-household ratio in a building, building construction year, and number of apartment in the community (natural logarithm form). The number of apartment is included due to the fact that it could explain the housing price in a certain level: the denser the community is, the lower living amenity could be, and the lower the housing price would be.

2.2.2.6 Neighbourhood characteristics

The neighbourhood facilities could influence the housing price regarding the quality and amenities residents could obtain from the surrounding neighbourhood. Individuals have substantial preference towards a neighbourhood with better environmental condition. Therefore, this study includes four neighbourhood: green and blue percentage in the 50 m radius circular neighbourhood, green and blue percentage between 50 - 200 m radius-ring neighbourhood, presence of highway in 300 m, presence of railway in 50 m. The first one is the view distance of green and blue from your own house which could directly impact your living quality as people prefer to have a view of green and blue for their psychological benefits. The second one (percentage of green and blue in 50 - 200 m) is the stroll or walking distance from one house that an individual could enjoy. And it is also summed as the daily view along the way when going out and coming back home. The other two variables could present the dis-amenities from traffic noise in the surrounding environment.

2.2.2.7 Location characteristics

The location of a house has significant impact on housing price as the proximity to the amenities differs in different location which influences an individual's value towards one house located in different locations. The location characteristics applies in his study include distance to the nearest highway entrance, distance to the nearest metro station, distance to city centre, distance to the nearest shopping centre, distance to the nearest park.

2.2.2.8 District fixed effect

As urban development level and the policies from the government differ towards different administration districts and similar inside each of them. To capture these group-effects and control for omitted variable bias due to unobserved heterogeneity when this heterogeneity is constant across different districts, the districts groups are applied in the hedonic pricing models in our study. These transaction observations from these seven districts are listed in Table 7.

Table 7 Observation summary of seven districts

District (Id)	Freq.	Percent	District (Id)	Freq.	Percent
Chaoyang (1)	172,351	38.26	Shijingshan (5)	12,833	2.85
Dongcheng (2)	27,7	6.15	Xicheng (6)	52,068	11.56
Fengtai (3)	94,051	20.88	Daxing (7)	17,249	3.83
Haidian (4)	74,273	16.49	Total	450,525	100

2.2.2.9 Park-zone fixed effect

In order to reveal the value of an urban park for a household by hedonic pricing, the heterogeneity between different park-specific zones need to be considered. Therefore, a park-zone fixed effect regarding a specific park service radius was applied to control the unobserved heterogeneity between different park influential areas in order to focus on the added value of proximity to a park in a park zone.

2.3 Hedonic pricing model

This study aimed at exploring the added value of urban parks for human wellbeing's daily life at different distances from a park. An approach of hedonic pricing models was conducted to investigate the importance of urban parks in residents' life by the housing price premium, which is also the extra price residents would pay for their houses in order to live closer to an urban park.

In order to investigate the value of an urban park by the housing price, two kinds of models were performed. At the first stage, a semi-parametric model was formed to access the general idea of a nearby park impact on house price. At the second stage, six log-linear models were applied in a further step based on the result from the first stage to investigate the precise impact of a nearby park on house price.

2.3.1 First stage: semi-parametric model

In order to investigate the impact of a nearby park to a household, one semi-parametric model was conducted at the first stage. The distance to the nearest park d_i from the i^{th} transaction house was performed as the non-parametric part as (1) the author would like to find out the influential distance threshold of the added value impact on the housing price from a nearby park when the specific distance threshold is not clear; (2) the function form of the housing price premium impact from park distance was unclear. Seven type of other control variables listed in Table were applied as the parametric part in this model. These variables were selected based on several previous studies regarding the hedonic housing price model and they are significantly linear correlated with the housing price. Therefore, these variables were included as the parametric part with a linear from model (1).

$$\begin{aligned} P_i = f(d_i) + \sum_{l=1}^{6} \beta_{Hl}\, Housing_{il} + \sum_{m=1}^{2} \beta_{Pm}\, Property_{im} + \sum_{n=1}^{4} \beta_{Cn}\, Construction_{in} \\ + \sum_{o=1}^{4} \beta_{No}\, Neighborhood_{io} + \sum_{p=1}^{4} \beta_{Lp}\, Location_{ip} + \sum_{q=1}^{7} \beta_{Dq}\, District_{iq} + \boldsymbol{\beta_Y YEAR_i} + \epsilon_i \end{aligned} \qquad (1)$$

P_i is the value of the i^{th} transaction price

$f(d_i)$ is the non-parametric function regarding the distance from the i^{th} transaction house to the nearest park (d_i)

$Housing_{il}$ is the i^{th} transaction's house's l^{th} housing-structural characteristic and β_{Hl} is the corresponding coefficient

$Property_{im}$ is the i^{th} transaction's house m^{th} property characteristic and β_{Hl} is the corresponding coefficient.

$Construction_{in}$ is the i^{th} transaction's n^{th} housing-construction characteristic and β_{Cm} is the corresponding coefficient.

$Neighborhood_{io}$ is the i^{th} transaction's o^{th} housing-neighbourhood characteristic and β_{No} is the corresponding coefficient.

$Location_{ip}$ is the i^{th} transaction's p^{th} housing-location characteristic and β_{Lp} is the corresponding coefficients.

$District_{iq}$ is the i^{th} transaction's q^{th} district dummy, if the i^{th} transaction's in the q^{th} district, the value of this variable would be 1, otherwise, 0. β_{Dq} is the corresponding coefficient.

$\boldsymbol{YEAR}_i$ is a $\mathrm{k} \times 1$ ($\mathrm{k} \in [1,10]$) vector of the i^{th} transaction's occurrence year. $\boldsymbol{YEAR}_{ki} = 1$ if the transaction occurred in the year $2000 + \mathrm{k}$.

$\boldsymbol{\beta_Y}$ is a $1 \times \mathrm{k}$ ($\mathrm{k} \in [1,10]$) vector of the corresponding coefficient.

ϵ_i is the error term

2.3.2 Second stage: log-linear model

To assist the analysis regarding the impact of the presence of a park from stage one, and the author conducted five log-linear hedonic pricing models in the second stage, three of them estimated the value of all parks on housing price, two of them conducted the valuation of large parks (large than 2 ha).

2.3.2.1 Valuation of all parks with district fixe effect

In the first three models, the distance to the nearest park performed as the variable of interest. The variables could impact the housing price these model controlled were the same as those in the previous stage. In order to confirm the influential distance thresholds pictured from the first stage and narrow down the thresholds to more specific distance values, this model was performed several trails. And the final 750 m influential threshold was applied in these models (2) (3), and (4) because this threshold generated best models with the highest R squares which could explain the housing price in the most sufficient way. Model (2) was conducted with the price as the dependent variable while model (3) and (4) were performed with ln(Price) as the dependent variable. Particularly, in model (4), the author applied distances to 4 classes of parks (Class 1 to Class 4 are parks with size from smallest to biggest) as our variables of interest in order to investigate different housing price premium impact from different classes of parks.

$$P_i = \beta_0 + \beta_d d_i + \sum_{l=1}^{6} \beta_{Hl}\, Housing_{il} + \sum_{m=1}^{2} \beta_{Pm}\, Property_{im} + \sum_{n=1}^{3} \beta_{Cn}\, Construction_{in} + \sum_{o=1}^{4} \beta_{No}\, Neighborhood_{io} + \sum_{p=1}^{4} \beta_{Lp}\, Location_{ip} + \sum_{q=1}^{7} \beta_{Dq}\, District_{iq} + \boldsymbol{\beta_Y YEAR_i} + \epsilon_i \quad (2)$$

$$lnP_i = \beta_0 + \beta_d d_i + \sum_{l=1}^{6} \beta_{Hl}\, Housing_{il} + \sum_{m=1}^{2} \beta_{Pm}\, Property_{im} + \sum_{n=1}^{3} \beta_{Cn}\, Construction_{in} + \sum_{o=1}^{4} \beta_{No}\, Neighborhood_{io} + \sum_{p=1}^{4} \beta_{Lp}\, Location_{ip} + \sum_{q=1}^{7} \beta_{Dq}\, District_{iq} + \boldsymbol{\beta_Y YEAR_i} + \epsilon_i \quad (3)$$

$$lnP_i = \beta_0 + \sum_{c=1}^{4} \beta_{dc}\, d_{ic} + \sum_{l=1}^{6} \beta_{Hl}\, Housing_{il} + \sum_{m=1}^{2} \beta_{Pm}\, Property_{im} + \sum_{n=1}^{3} \beta_{Cn}\, Construction_{in} + \sum_{o=1}^{4} \beta_{No}\, Neighborhood_{io} + \sum_{p=1}^{4} \beta_{Lp}\, Location_{ip} + \sum_{q=1}^{7} \beta_{Dq}\, District_{iq} + \boldsymbol{\beta_Y YEAR_i} + \epsilon_i \quad (4)$$

d_{ic} is the distance from the i^{th} transaction house to the nearest i^{th} class park.

β_{dc} the corresponding coefficient.

2.3.2.2 Valuation of large parks with park-zone fixed effect

After the previous three models, the author found large parks could have higher influence on housing price. Therefore, 56 large parks from class 3 and 4 were selected to conduct further estimation. In order to control the unobserved heterogeneity between parks, this study applied the large park 750 m radius park-zone fixed effect. Model (5) was conducted with the linear distance to the nearest large park as the variable of interest. Model (6) was conducted with different distance intervals, 0-100m, 100-300m, 300-500m, 500-700m, and 700-750m (the reference interval).

$$lnP_i = \beta_0 + \beta_{dL} d_{iL} + \sum_{l=1}^{6} \beta_{Hl}\, Housing_{il} + \sum_{m=1}^{2} \beta_{Pm}\, Property_{im} + \sum_{n=1}^{3} \beta_{Cn}\, Construction_{in} + \sum_{o=1}^{4} \beta_{No}\, Neighborhood_{io} + \sum_{p=1}^{4} \beta_{Lp}\, Location_{ip} + \sum_{r=1}^{56} \beta_{PZr}\, ParkZ_{ir} + \boldsymbol{\beta_Y YEAR_i} + \epsilon_i \quad (5)$$

$$lnP_i = \beta_0 + \sum_{l=1}^{5} \beta_{Ik}\, In_{ik} + \sum_{l=1}^{6} \beta_{Hl}\, Housing_{il} + \sum_{m=1}^{2} \beta_{Pm}\, Property_{im} + \sum_{n=1}^{3} \beta_{Cn}\, Construction_{in} + \sum_{o=1}^{4} \beta_{No}\, Neighborhood_{io} + \sum_{p=1}^{4} \beta_{Lp}\, Location_{ip} + \sum_{r=1}^{56} \beta_{PZr}\, ParkZ_{ir} + \boldsymbol{\beta_Y YEAR_i} + \epsilon_i \quad (6)$$

d_{iL} is the distance from the i^{th} transaction house to the nearest large park (including class 3 and class 4).

β_{dL} is the corresponding coefficient.

$Park_{ir}$ is the i^{th} transaction's r^{th} park-zone dummy, if the i^{th} transaction's in the r^{th} park-zone. The value of this variable would be 1, otherwise, 0.

β_{PZr} is the corresponding coefficient.

In_{ik} is the i^{th} transaction's k^{th} park distance interval dummy, if the i^{th} transaction's in the k^{th} interval, the value of this variable would be 1, otherwise, 0.

β_{Ik} is the corresponding coefficient.

3 Regression results

3.1 First stage results of semi-parametric model

A graph showing between housing price and distance from the nearest park is generated by the In Fig. 3, the result of the semi-parametric model (1) was shown with the predicted housing price (expressed in Chinese yuan) decreasing with the distance from the nearest park. A more detailed regression result is added in Appendix C.1. To check the fitness level of the model, the author compared the regression results of the model with the actual housing price value by calculating the maximum and minimum values of the average value of 100 bootstrap replicates from all the actual transaction prices at each specific house-park distance. The upper bound price is the maximum average price and the lower bound price is the minimum average price. It is shown the model works well for our housing transaction data in the distance interval 0-750m since the solid line is between the upper bound and lower bound dot lines in this part. This indicates within 750 m from the nearest park, the model could perform well and predict the housing price close to the average actual price. After this threshold, the housing price from the observations would fluctuate substantially. Therefore, the author adopted this 750 m as the park influential threshold which is the best suitable for our dataset in our case study in the second and third stages.

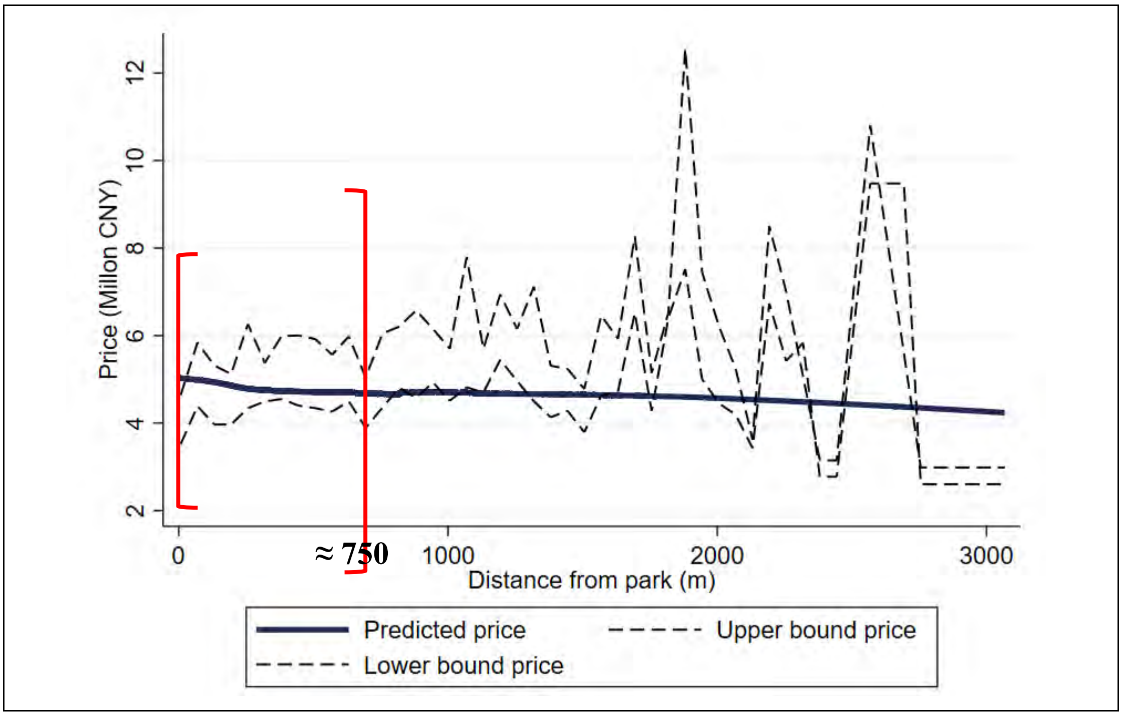


Fig. 3 Predicted housing price with distance to the nearest park (m)

3.2 Second stage results of log-linear models

3.2.1 District fixed effect models for all parks

To assist the analysis regarding the impact of the presence of a park from stage one, and to dig deeper a more precise impact of an urban park to the nearby housing price, the author firstly conducted three log-linear models with the observations in the distance of 750 m to the nearest park. This estimation was conducted with the district fixed effect to control the unobserved heterogeneity between different administration districts.

The regression results regarding the coefficients between park proximity with respect to the park distance are shown in the Table 8. More detailed results are presented in Appendix C.2. These models confirmed the results from the first stage: the larger the distance between a house from a nearest park, the lower the house price will be. Generally speaking with the transaction records within a distance of 750 m radius from the nearest park, when the distance increases 100 m, the housing price would drop 40162 yuan (5020 euros) as shown in Model (2) and 0.443% as shown in Model (3). Model (4) was performed with parks in 4 classes to investigate how parks with different scales could impact the housing premium differently. As shown in Table 8, the biggest park (class 4) has the most economically positive impact on the housing price of a nearby house. It could increase 0.106% of the housing price when its proximity to a park increases 100 m.

3.2.2 Park-zone fixed effect models for large parks

Based on the results from Model (4), larger parks could promote the nearby housing price in a large extent, therefore, a further investigation regarding the impact of large parks (with a size larger than 20 ha) was conducted by Model (5) and (6). The 750 m park-zone fixed effect was introduced in both models to control the unobserved heterogeneity between each park-zone areas. Different from Model (2) and (3), only observations located in the 56 park-zones (expressed in green colour in Fig.4) were included. Model (5) is a linear distance model and Model (6) is an interval dummy distance model. The regression result is shown in Table 8 and a more detailed result table is list in Appendix C.3. With the liner corelation between the distance to the nearest large park and the housing price, it is shown that the housing price would decrease 0.752% when the distance to a park increases 100 m. Model (6) shows the value of a large park to a nearby house would be the largest (5.17%) in the nearest distance interval, 0-100 m. As distance increases, the impact of the housing price premium decays (Fig. 5).

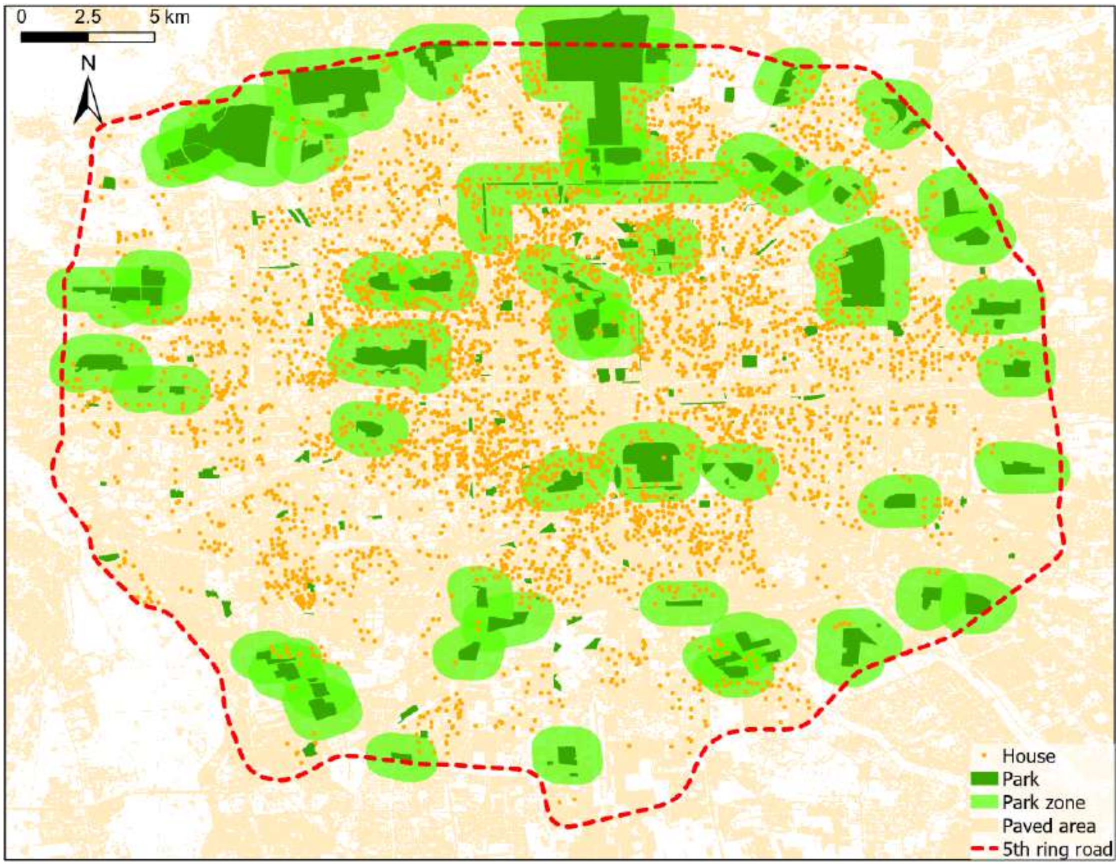


Fig. 4 750m influential park-zone of 56 large parks (class 3 and class 4)

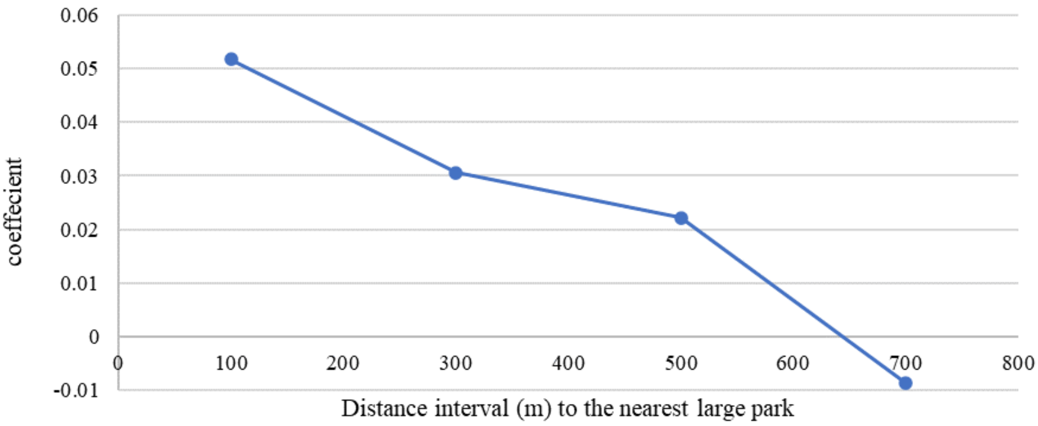


Fig. 5 Coefficient of the presence of a large park in different park-house distance intervals

Table 8 The nearest park impact on the nearby the housing price within 750 m distance

	District fixed-effect			Park-zone fixed effect	
Models	(2)	(3)	(4)	(5)	(6)
Class of parks	All parks Price	All parks ln(Price)	Park Class1-4 ln(Price)	Large parks ln(Price)	Large parks ln(Price)
Variable of interest					
Dist. Park (100 m)	**-40,162*****	**-0.00443*****			
	(1,736)	(0.000197)			
Dist. Class1 Park (100 m)			**0.000496*****		
			(0.0000381)		
Dist. Class2 Park (100 m)			**-0.000526*****		
			(0.0000586)		
Dist. Class3 Park (100 m)			**0.000349*****		
			(0.0000410)		
Dist. Class4 Park (100 m)			**-0.00106*****		
			(0.0000263)		
Dist. Large park (100 m)				**-0.00752*****	
				(0.000327)	
Dist. Interval: Large park					
0-100 m					**0.0517*****
					(0.00408)
100-300 m					**0.0306*****
					(0.00262)
300-500 m					**0.0222*****
					(0.00254)
500-700 m					**-0.00854*****
					(0.00251)
Other variables					
Ln(floorspace)	**0.000003432 *****	**0.777*****	**0.777*****	**0.815*****	**0.815*****
	(26,063)	(0.00257)	(0.00257)	(0.00421)	(0.00420)
Year dummies	YES	YES	YES	YES	YES
Housing dummies	YES	YES	YES	YES	YES
Property dummies	YES	YES	YES	YES	YES
Construction dummies	YES	YES	YES	YES	YES
Neighbourhood dummies	YES	YES	YES	YES	YES
Location conditions	YES	YES	YES	YES	YES
Constant	**-0.0000007657 *****	**-5.883*****	**-5.941*****	**-9.096*****	**-8.413*****
	(900,099)	(0.119)	(0.119)	(0.207)	(0.207)
Num. Fixed effect groups	7	7	7	56	56
Observations	285,036	285,036	285,036	101,482	101,479
R-squared	0.741	0.882	0.883	0.911	0.911

Notes: Dependent variable in Model (2) is transaction price and that in Model (3) (4) (5), and (6) is natural logarithm (transaction price in Chinese yuan).
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

4 Discussion

Based on the research conducted with the hedonic pricing models estimating the hosing price premium impacted by a nearby urban park in central Beijing area, this study found significant and convincing results regarding all of the six models applied in our research. 0.44% housing price increases when the distance to a park decreases 100 m, or 20, 907 yuan (2,613 euros) with the average price (4,719,436 yuan). The housing price premium impact from large parks is even higher, that is 0.75 % when the distance to a park increases 100 m, or 35,490 yuan (4,436 euros) with the average price. The magnitude of the price increase might be relatively small compare to many other case studies, the total housing price premium in a park influential area would be substantial as the apartment density in central Beijing area is much larger compare to other cities around the world.

The influential threshold was found as 750 m from a park which is relatively a large influential radius compare to some other studies, for instance a 75 m threshold of an open space impact on housing price was found by Dekkers & Koomen, (2013). The reason could be the density of urban parks in Beijing is relatively lower due to the higher residential density. This leads to an urban park would still be beneficial for residents living one or two blocks away from this park.

Other than the findings from this case study, some issues the author would like to discuss and might do further investigate as well. The first one is why the housing price would still go up when a house located further than 750 m away from a park shown in Model (1), the demi-parametric model? There should be some other omitted variables could be considered as control variables in the models. Probably an explanation could be a large park might have an influential radius further than 750 m where residents still benefit by living in a metro accessible distance. This result might also because that these large parks are mostly clustered close to the city centre.

In the hedonic models applied, the houses' coordination is the same if they are located in same community. This study circuited this problem by adding community characteristics (property service fee and number of apartment) which is helpful to differentiate the housing prices from different communities, and to control other variables affecting housing price with similar (or same) distance differences from the nearest park. Moreover, the general community housing transaction dataset (7,191 communities) with average transaction prices could also be conducted as a compassion study in the further research. In such way, the focus would be more on to the spatial related impacts, such as the park distance, rather than micro scope of housing characteristic related impacts. The value of spatial characteristics could be more clear with controlling the unobserved heterogeneity when this heterogeneity is constant in each community. Therefore better implementation based on the analysis from these preference towards urban parks would be possible. This could lead to creating a social optimal urban.

5 Conclusion

This study found a significant coefficient between urban parks and the nearby housing price in the housing market of central Beijing areas. And this housing price premium is even higher from large parks. It also revealed the promoting magnitude decays when the distance to a park increases.

This study delivered a specific hedonic pricing study to estimate the added value of an urban park to a nearby household in the housing market of central Beijing areas. From this study, we could better find the influential radius from an urban park and further investigate the magnitude of a large urban park's impact on a nearby housing price. And in this way, the total benefit could be calculated if we know the total household in the park influential radius. One step further, with a cost-benefit analysis when including the construction cost of an urban park and the opportunity cost of a more profitable land use type, the optimal location to construct an urban park could be chosen. This is helpful for a more appreciable urban planning in the future to improve the social welfare and sustainable development practically.

From the academic aspect, the two-stage process with different types of hedonic pricing models to investigate the value of an urban park to a household set up an integrated model for further research in this urban park valuation research field. This hedonic process could also be applied in other research field regarding the valuation from human beings. Furthermore, with this research, more research could be conducted to investigate how different park characteristics could impact the value of an urban park.

Appendix A. Datasets introduction

A.1 land cover

Land cover is from the dataset of FORM-GLC10 (Finer Resolution Observation and Monitoring of Global Land Cover 2017 10-m resolution) shown in Fig. A1.

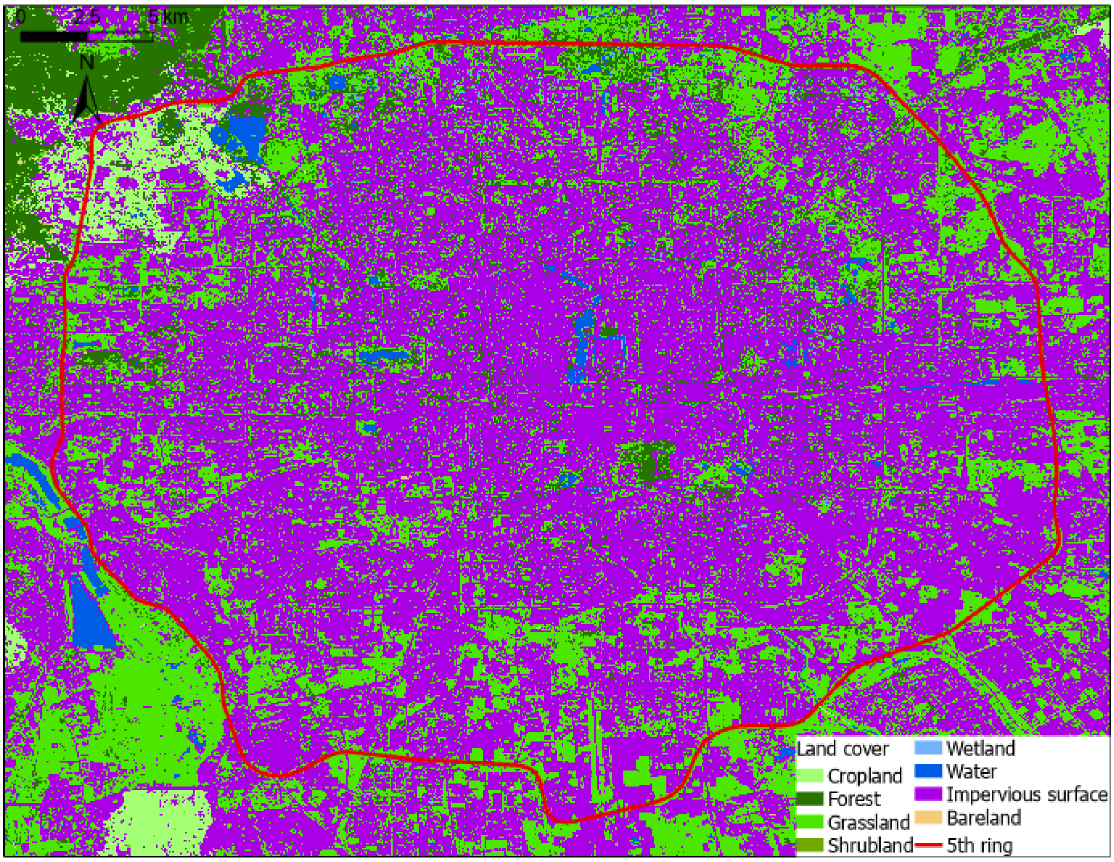


Fig. A1. Land cover from FROM-GLC10 dataset

A.2 Housing dataset

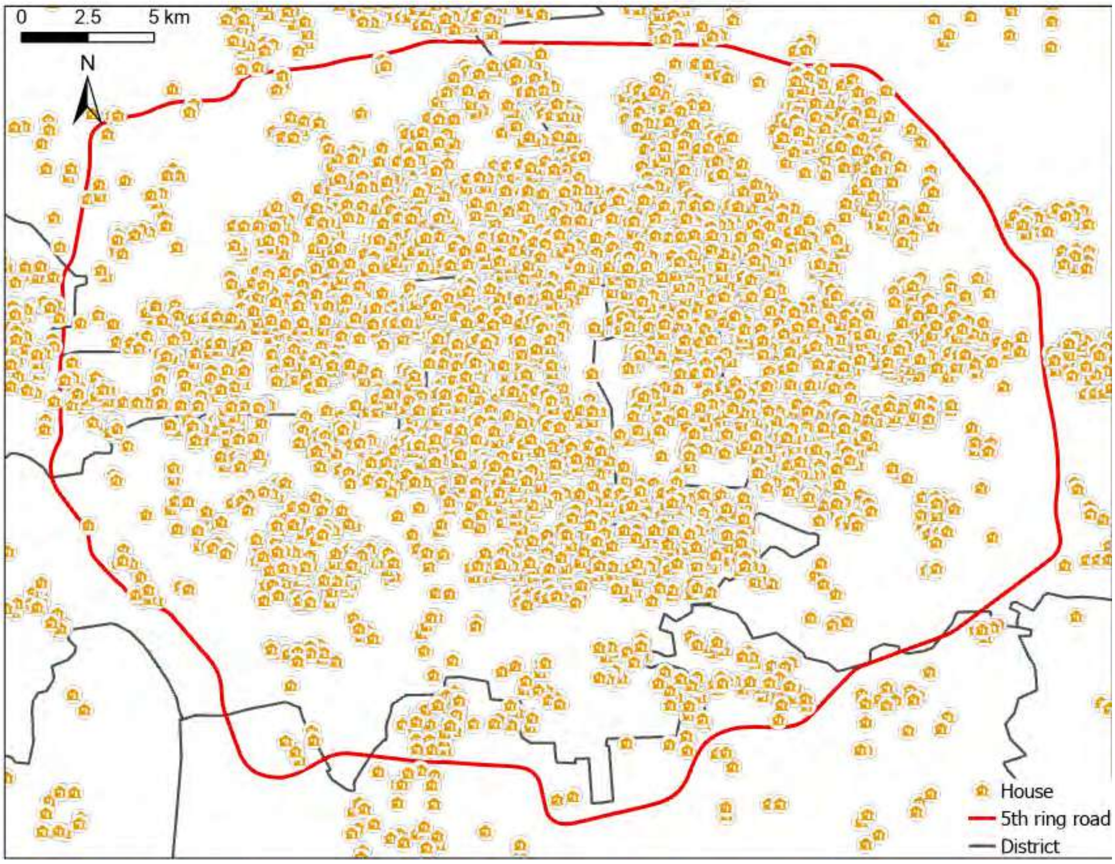


Fig. A2. Housing dataset generated by the author

A.3 POI (Points of Interest)

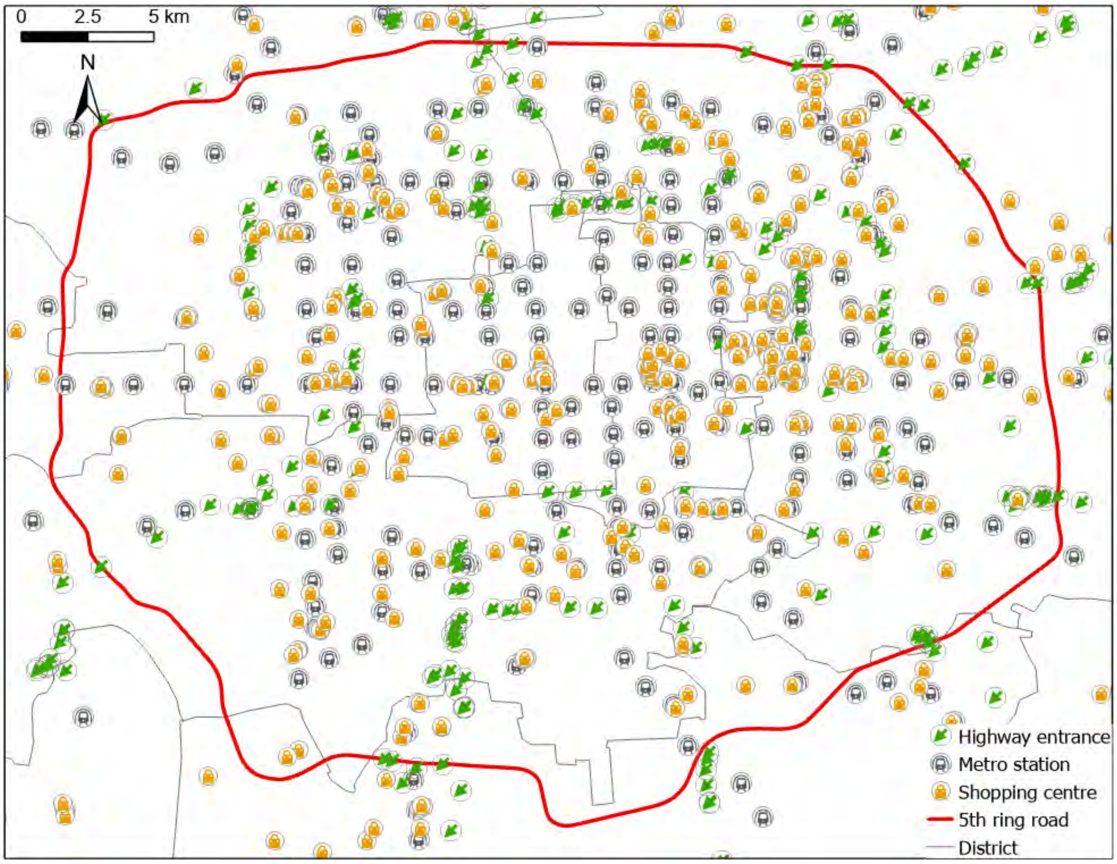


Fig. A3. Point of interest generated by the author from Baidu Map API

Appendix B. Housing dataset cleaning process

B.1 Clean outliers

The author cleaned the data by dropping outliers for total price, floorspace, and average price per square meter. The cut-off values regarding floorspace are 10m^2 and 800 m^2. The lower bound cut-off values regarding housing price are 50000 yuan (6,250 euros) as the transaction price and 5000 yuan (625 euros) per m^2. 113 observation were dropped as outliers outside of the range of cut-off values.

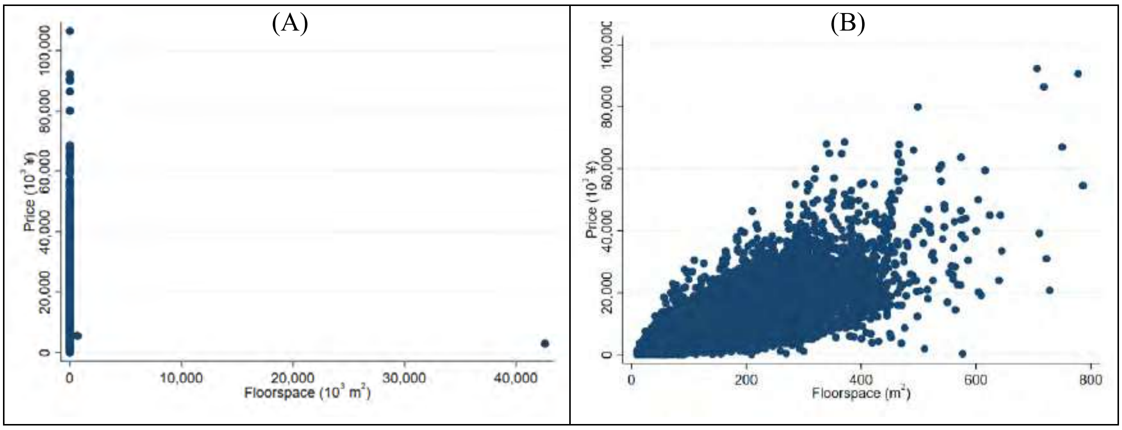
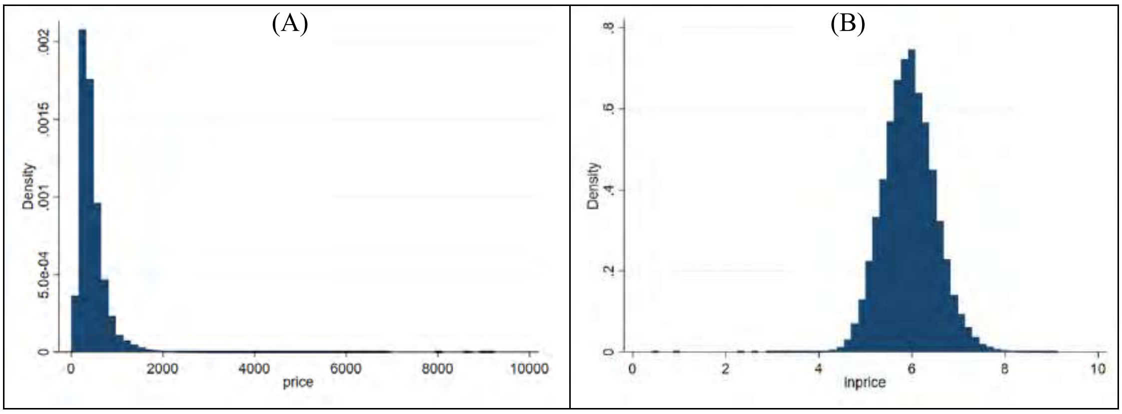


Fig. B1 Plots of housing price with floorspaces before (A) and after (B) data cleaning

B.2 Check variable distribution

By checking the distribution of price and floorspace, it was found the housing price and floorspace are right screwed distributed. Therefore, the author applied the logarithm of both variables to generate relative normal distributed variables in most of the models.



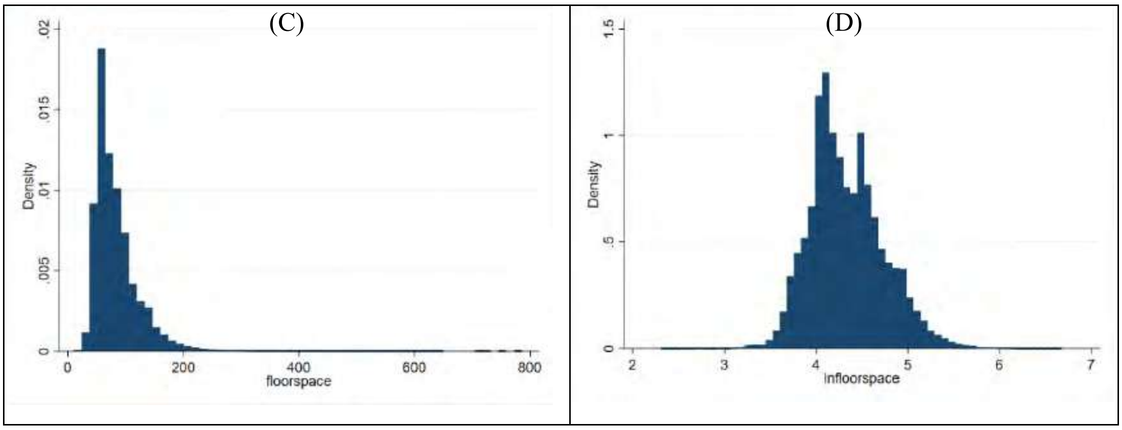


Fig. B2 Distributions of housing price (A), ln(price) (B), floorspace (C), and ln(floorspace) (D)

Appendix C. Detailed housing model results

C.1 Stage one: Semi parametric regression results

Table 9 Regression results of semi-parametric model with district-fixed effect

Model VARIABLES	(1) District FE Price
Housing variable	
Ln(floorspace)	0.00000494***
	(26,675)
Num. rooms	134,201***
	(4,059)
House type - Reference type: Apartment	
Villa	-156,825*
	(84,664)
Courtyard	0.000003912***
	(209,385)
Bungalow	0.000002145***
	(259,521)
Service Apart.	0.000008101***
	(0.000001141)
Level type - Reference type: Middle	
Low	-68,311***
	(5,584)
Basement	-0.000001348***
	(38,098)
Bottom	-85,029***
	(8,227)
Unknown	-538,498***
	(43,417)
Top	-166,294***
	(7,240)
High	2,531
	(5,396)
Decoration type - Reference type: Rough	
Simple	-187,786***
	(15,151)
Deluxe	-82,062***
	(5,863)
Other	53,409***
	(5,658)
Direction - Reference type: East	
Northeast	22,762
	(14,216)
Southeast	307,324***
	(9,835)
North	-26,254
	(18,090)
South	137,369***
	(6,779)
West	-62,723***
	(9,440)
Northwest	-6,514
	(15,377)
Southwest	264,379***
	(10,385)
None	77,190
	(74,271)
Property variable	

Ownership right type **-** Reference type: class I economical	
Village	-634,829
	(0.000001133)
Class II economical	133,134***
	(32,921)
Using right	0.000002228***
	(435,877)
Public rental	229,475**
	(111,171)
Military estates	-0.000001273**
	(507,296)
Commercial	94,818***
	(26,738)
Central government	261,376***
	(31,358)
Orientation placement	500,319*
	(284,496)
Purchased housing	-6,423
	(27,701)
School housing	-202,025
	(654,598)
Personal housing	374,231***
	(32,813)
Self-built housing	683,073
	(0.000001133)
Low-cost commercial	88,531
	(77,710)
Property service fee	291,730***
	(7,508)
Construction variable	
Pres. Lift	-476.7
	(12,563)
Lift-house ratio	245,508***
	(15,933)
Construction year	10,898***
	(811.4)
Ln(Num. apartment)	-175,381***
	(18,668)
Neighbourhood variable	
% green and blue 50m	0.000001943***
	(116,369)
% green and blue 50-200m	0.000003137***
	(201,190)
Pres. of highway in 300m	-232,321***
	(41,946)
Pres. of railway in 50m	-415,246***
	(103,294)
Location variable	
Dist. city centre (km)	-45,061***
	(9,306)
Dist. shopping centre (km)	331,860***
	(43,666)
Dist. highway entrance (km)	-183,309***
	(27,023)
Dist. metro station (km)	-41,360
	(48,787)
Year dummies	YES
District fixe effect	YES
Observations	451,039
R-squared	0.655

Notes: Dependent variable in all models (1) is transaction price and that in the other 2 models is natural logarithm (transaction price in Chinese yuan). This model was estimated with Stata's plreg command, a bandwidth of 0.8 was used as default.
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

C.2 Second stage: Park general impact in different distance intervals

Table C.2 Park general impact regression with districts fixed effect

VARIABLES	(2) All parks Price	(3) All parks ln(Price)	(4) Class 1-4 parks ln(Price)	(5) Large parks ln(Price)	(6) Large parks ln(Price)
Variable of interest					
Dist. Park (100 m)	-401.6***	-0.0000443***			
	(17.36)	(0.000001.97)			
Dist. C1 Park (100m)			0.00000495***		
			(0.000000381)		
Dist. C2 Park (100m)			-0.00000528***		
			(0.000000586)		
Dist. C3 Park (100m)			0.00000349***		
			(0.000000410)		
Dist. C4 Park (100m)			-0.0000106***		
			(0.000000257)		
Dist. Large park (100 m)				-0.0000752***	
				(0.00000327)	
Large parks interval - reference type: 700-750 m					
0-100 m					0.0517***
					(0.00408)
100-300 m					0.0306***
					(0.00262)
300-500 m					0.0222***
					(0.00254)
500-700 m					-0.00854***
					(0.00251)
Housing variable					
Ln(floorspace)	0.000003432***	0.777***	0.777***	0.815***	0.814***
	(26,063)	(0.00257)	(0.00257)	(0.00421)	(0.00423)
Num. rooms	527,545***	0.0429***	0.0430***	0.0320***	0.0323***
	(8,962)	(0.000697)	(0.000695)	(0.00108)	(0.00108)
House type – Reference type: Apartment					
Villa	6.232e+06***	0.298***	0.297***		
	(641,150)	(0.0197)	(0.0199)		
Courtyard	4.968e+06***	0.591***	0.603***		
	(478,370)	(0.0479)	(0.0478)		
Bungalow	1.485e+06*	0.135	0.141		
	(785,976)	(0.167)	(0.168)		
Service Apart.	8.428e+06***	0.471***	0.481***		
	(1.597e+06)	(0.0382)	(0.0382)		
Level type – Reference type: Middle					
Low	-99,417***	-0.0128***	-0.0127***	-0.0123***	-0.0124***
	(8,103)	(0.000969)	(0.000966)	(0.00140)	(0.00139)
Basement	-1.292e+06***	-0.362***	-0.360***	-0.411***	-0.411***
	(73,395)	(0.00897)	(0.00908)	(0.0133)	(0.0133)
Bottom	24,439*	-0.00242	-0.00219	-0.00458**	-0.00488**
	(13,906)	(0.00155)	(0.00154)	(0.00230)	(0.00230)
Unknown	-547,660***	-0.0196**	-0.0204**	-0.000277	-0.00170
	(70,389)	(0.00868)	(0.00865)	(0.0129)	(0.0128)

Top	-212,428***	-0.0576***	-0.0576***	-0.0524***	-0.0525***
	(10,833)	(0.00128)	(0.00128)	(0.00194)	(0.00194)
High	-63,665***	-0.0109***	-0.0108***	-0.00855***	-0.00852***
	(8,365)	(0.000960)	(0.000958)	(0.00139)	(0.00139)
Decoration type - Reference type: Rough					
Simple	-257,489***	-0.0417***	-0.0424***	-0.0281***	-0.0279***
	(29,532)	(0.00307)	(0.00307)	(0.00469)	(0.00468)
Deluxe	-327,018***	-0.0347***	-0.0352***	-0.0279***	-0.0277***
	(10,766)	(0.00131)	(0.00130)	(0.00209)	(0.00209)
Other	35,015***	0.0188***	0.0179***	0.00938***	0.00960***
	(11,926)	(0.00129)	(0.00129)	(0.00201)	(0.00201)
Direction - Reference type: East					
Northeast	-147,375***	-0.00831***	-0.00772***	-0.00528	-0.00536
	(18,757)	(0.00263)	(0.00263)	(0.00377)	(0.00376)
Southeast	192,747***	0.0322***	0.0312***	0.0401***	0.0405***
	(15,915)	(0.00176)	(0.00177)	(0.00272)	(0.00272)
North	282,959***	-0.00972***	-0.00944***	-0.0431***	-0.0435***
	(14,926)	(0.00237)	(0.00235)	(0.00366)	(0.00365)
South	344,696***	0.0554***	0.0561***	0.0620***	0.0622***
	(8,549)	(0.00102)	(0.00101)	(0.00156)	(0.00156)
West	-116,935***	-0.0282***	-0.0286***	-0.0280***	-0.0283***
	(11,463)	(0.00169)	(0.00168)	(0.00255)	(0.00255)
Northwest	-161,931***	-0.0142***	-0.0133***	-0.0126***	-0.0126***
	(20,293)	(0.00273)	(0.00272)	(0.00373)	(0.00371)
Southwest	105,148***	0.0258***	0.0244***	0.0299***	0.0300***
	(15,312)	(0.00180)	(0.00180)	(0.00265)	(0.00264)
None	358,944	-0.0902**	-0.0901**	-0.100*	-0.100*
	(287,601)	(0.0451)	(0.0451)	(0.0519)	(0.0521)
Property variable					
Ownership right type - Reference type: Class I economical					
Village	571,490***	0.290***	0.283***		
	(46,935)	(0.00791)	(0.00773)		
Class II economical	723,549***	0.0951***	0.0902***	0.0507***	0.0498***
	(48,169)	(0.00854)	(0.00838)	(0.0120)	(0.0120)
Using right	3.408e+06***	0.340***	0.356***	0.00773	0.00927
	(283,612)	(0.0483)	(0.0474)	(0.0905)	(0.0897)
Public rental	1.230e+06***	0.0826***	0.0861***	0.121	0.125
	(180,757)	(0.0286)	(0.0299)	(0.0949)	(0.0922)
Military estates	-825,311	-0.173	-0.196		
	(688,212)	(0.156)	(0.154)		
Commercial	1.164e+06***	0.146***	0.143***	0.0723***	0.0722***
	(43,514)	(0.00762)	(0.00745)	(0.0101)	(0.0101)
Central government	1.316e+06***	0.205***	0.199***	0.0996***	0.100***
	(49,016)	(0.00826)	(0.00811)	(0.0112)	(0.0112)
Orientation placement	1.389e+06***	0.219***	0.209***		
	(141,685)	(0.0241)	(0.0246)		
Purchased housing	965,921***	0.160***	0.156***	0.0993***	0.0987***
	(43,969)	(0.00773)	(0.00756)	(0.0103)	(0.0104)
School housing	191.4	0.0842**	0.0700**	0.0574	0.0601
	(212,194)	(0.0343)	(0.0343)	(0.0442)	(0.0440)
Personal housing	1.497e+06***	0.147***	0.143***	0.0770***	0.0764***
	(64,530)	(0.00847)	(0.00831)	(0.0115)	(0.0115)
self-built housing	396,522***	0.155***	0.174***	-0.0244	-0.0275
	(48,312)	(0.00814)	(0.00802)	(0.0169)	(0.0169)
Low-cost commercial	76,526	-0.0608***	-0.0492***		
	(76,603)	(0.0129)	(0.0128)		

Property service fee	32,905***	0.00153***	0.00127***	0.0146***	0.0147***
	(1,934)	(0.000156)	(0.000157)	(0.000621)	(0.000622)
Construction variable					
Pres. Lift	182,142***	0.0225***	0.0204***	-0.00768***	-0.00892***
	(7,816)	(0.00102)	(0.00102)	(0.00164)	(0.00163)
Lift-house ratio	764,567***	0.0137***	0.0127***	-0.00556**	-0.00962***
	(26,905)	(0.00185)	(0.00184)	(0.00241)	(0.00240)
Construction year	30,489***	0.00377***	0.00378***	0.00573***	0.00555***
	(470.1)	(6.17e-05)	(6.15e-05)	(0.000107)	(0.000106)
Ln(Num. apartment)	-118,000***	-0.0108***	-0.00982***	-0.0159***	-0.0139***
	(3,838)	(0.000461)	(0.000463)	(0.000779)	(0.000777)
Neighbourhood variable					
% green and blue 50m	415,517***	0.0652***	0.0626***	0.139***	0.140***
	(18,330)	(0.00209)	(0.00208)	(0.00328)	(0.00328)
% green and blue 50-200m	2.043e+06***	0.335***	0.333***	0.200***	0.191***
	(39,857)	(0.00383)	(0.00383)	(0.00612)	(0.00616)
Pres. of highway in 300m	-103,553***	-0.0361***	-0.0339***	-0.0408***	-0.0475***
	(7,128)	(0.000836)	(0.000852)	(0.00152)	(0.00152)
Pres. of railway in 50m	-80,499***	-0.0348***	-0.0394***	0.0247***	0.0197***
	(17,335)	(0.00226)	(0.00221)	(0.00319)	(0.00318)
Location variable					
Dist. city centre (km)	-72,139***	-0.00860***	-0.00643***	-0.0686***	-0.0646***
	(1,802)	(0.000197)	(0.000235)	(0.000858)	(0.000857)
Dist. shopping centre (km)	-110,083***	-0.0153***	-0.00977***	0.0494***	0.0514***
	(8,959)	(0.00103)	(0.00104)	(0.00216)	(0.00215)
Dist. highway entrance (km)	-200,775***	-0.0450***	-0.0397***	-0.0219***	-0.0253***
	(4,642)	(0.000572)	(0.000595)	(0.00168)	(0.00168)
Dist. metro station (km)	-195,774***	-0.0512***	-0.0545***	-0.0326***	-0.0357***
	(9,013)	(0.00107)	(0.00111)	(0.00248)	(0.00249)
Year dummies	YES	YES	YES	YES	YES
Fixed effect	District	District	District	Park-zone	Park-zone
Num. fixed effect	7	7	7	56	56
Constant	-7.657e+07***	-5.883***	-5.941***	-9.096***	-8.222***
	(900,099)	(0.119)	(0.119)	(0.207)	(0.205)
Observations	285,036	285,036	285,036	101,482	101,479
R-squared	0.741	0.882	0.883	0.911	0.912

Notes: Dependent variable in Model (2) is transaction price and that in Model (3) and (4) is natural logarithm (transaction price in Chinese yuan).
Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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