Valuing Ecosystem Services: Exploring the Impact of Urban Green Spaces on the Housing Market

Abstract

In our research, we employ the hedonic pricing method and the difference in differences approach to examine the economic impact of urban green spaces on housing prices in Tehran, the capital of Iran. The hedonic pricing method estimates housing prices as a function of housing characteristics, neighborhood, and environmental variables. We contribute to the literature by enhancing our model with a refined set of variables, improved model specifications, and incorporating spatial correlation considerations among observations. Our commitment to a thorough investigation extends to assessing the unique effects of park type, size, and geographical locations. Additionally, we delve into the distributional impacts by considering the demographic characteristics of households in the regions, with a particular focus on their income levels. We employ GIS software to analyze the distances of houses in specific regions from local amenities. our results indicate a positive relationship between housing prices and proximity to parks of all sizes in affluent regions, while green spaces may lower house prices in less affluent regions, especially the large ones. Housing inflation further moderates this effect, indicating that as housing prices rise, the positive impact of parks diminishes. Additionally, using the difference in differences method, our study reveals that the construction of a midsize park in rich regions results in a 2% - 4% increase in neighboring house prices while it decreases between 2.5% to 6% in less affluent regions. These findings suggest wealthier individuals invest more in environmental amenities, classifying green spaces as luxury goods.

Keywords: Non-market valuation, Hedonic pricing method, Real state market, Urban green spaces, Geographic information system

1 Introduction

There are numerous benefits to urban green spaces, including air quality improvement, carbon sequestration, recreational opportunities, and energy savings due to the shading of buildings. Furthermore, they can enhance urban life by providing aesthetic benefits or flood control. For example, trees can improve the landscape quality of a neighborhood, or even a small plant in an office can enhance its beauty. Moreover, green spaces can reduce stress, protect residents from the adverse effects of undesirable land use, and promote local business by creating an area where people gather. Parks, in addition to these benefits, have several disadvantages, including congestion in the parks' surrounding environment. Furthermore, parks may pose a threat to the safety of individuals. Depending on the characteristics of each neighborhood, they can serve as sites for criminal activities, such as robbery and drug dealing.

It is crucial to understand that parks have positive and negative impacts on communities, so comprehensive studies are required to understand how one set of effects may dominate the other. This understanding is essential for policymakers to decide between environmental protection and land development; As communities become more urbanized, open space often diminishes, and the public benefits it offers decrease as well. Understanding the economic advantages of accessing open space can help planners make informed decisions about the balance between conserving these areas and permitting urban development. This study takes a small step to shed light on the value of parks in urban areas. We aim to determine the value of parks to the communities and how they affect house prices.

There are numerous discussions regarding the primary use of the hedonic pricing method, but it was undoubtedly expanded and developed by Rosen in 1974. Following this, Freeman (1979 and 1985) and Palmquist(1991) extended its application. This method is not limited to environmental discussions, and it can be applied in other fields where non-market goods exist, such as health economics. Most studies that examine the effects of environmental amenities use the hedonic pricing method, and the differences are mainly related to the functional forms, especially the linear and semi-logarithmic forms. Variations in results often result from spatiotemporal differences.

Most studies support the idea that parks positively influence house prices. These effects vary in the type and size of green spaces. For example, Tyrvainen(1997) stated that urban forests are substantial environmental amenities, and their benefits are reflected in housing prices. Proximity to forested areas, water runoff, and an increase in the proportion of forested land in residential areas all positively impact apartment prices. However, the direct influence of small forest parks on housing prices remains uncertain. Furthermore, Anderson and West(2006) showed the positive effect of urban parks, golf courses, lakes, and rivers and the negative impact of cemeteries on house prices in Paul. In addition, Larson and Perrings (2013) found that proximity to large parks and bodies of water increases housing prices in the urban area of Phoenix, while proximity to agricultural lands decreases them.

Moreover, Sander et al. (2010) used the percentage of green space as an environmental variable. They also conducted several tests related to heteroscedasticity and spatial autocorrelation. The latter refers to the concept that housing prices depend not only on their own characteristics but also on the features of neighboring houses. This study showed that green spaces are valuable to buyers, and higher percentages of greenery increase housing prices.

In addition, Czembrowski and Kronenberg (2016) classified green spaces into nine categories based on their size and equipment. They addressed the issue of spatial autocorrelation and showed that large parks had a significant impact on housing prices. However, small forest parks and large forests have no noticeable effect. Furthermore, Laszkiewicz et al. (2019) provided an analysis of the apartment market in Lodz, a city in Poland, based on the hedonic pricing method to find whether the marginal willingness to pay (MWTP) for proximity to parks and forests varies among different apartment price segments. They found that the share of the estimated MWTP for park proximity increases with the wealth of the apartment buyers. Consequently, they interpreted this as indicating that parks can be considered a luxury good.

In sum, prior studies have shown that urban green spaces provide valuable benefits to communities, but do not fully address which aspects of them are most valuable. Additional studies help to increase our understanding of the value of urban green spaces. This study aims to improve our understanding of the values for green spaces by eliciting information about the spatial pattern of benefits to residential property values as well as how values vary with different distance to the nearest park. In so doing, we also aim to determine whether urban green spaces affect house prices according to the specific characteristics of the local neighborhood and eventually uncover evidence of their advantages and disadvantages.

To the best of our knowledge, this paper stands as one of the pioneering studies, if not the first, to systematically investigate the influence of urban green spaces on the housing market in Tehran, the capital city of Iran. Our research endeavors to unravel the intricate relationship between environmental amenities and residential housing prices, employing the hedonic pricing method and the difference in differences identification technique.

In our pursuit, we employ GIS software to analyze the distances of houses in specific regions from local amenities. Beyond this, we make substantial contributions to the literature by enhancing our model with a refined set of variables, improved model specifications, and the incorporation of spatial correlation considerations among observations. Our commitment to a comprehensive study extends to evaluating the distinct effects of park type, size, and their geographical locations. Furthermore, we delve into the distributional effects based on the demographic characteristics of households in the regions, particularly their income levels.

A pivotal aspect of our research involves a classification of urban districts in Tehran into two distinct groups—those classified as rich and those deemed less affluent. This classification not only enriches the depth of our analysis but also provides a nuanced understanding of the varied economic landscapes within the city and to unravel the nuanced preferences and priorities of diverse homebuyers. In essence, our study aspires to contribute substantively to the evolving discourse on the impact of green spaces on housing dynamics, introducing a novel and comprehensive perspective to the existing body of knowledge. Additionally, we employ the difference in differences method to establish a causal relationship between proximity to parks and housing prices. This method serves as a valuable tool in mitigating endogeneity issues arising from omitted variables, enhancing the reliability and validity of our causal inferences.

The remainder of this paper is structured as follows: Section 2 describes empirical methodology in details and section 3 explains the collection and processing of the data into variables. The results are described in Section 4, followed by a discussion of the findings in the context of the valuation of urban green spaces in Section 5.

2 Methodology

2.1 Hedonic Pricing Method

Hedonic pricing method widely utilized to estimate the value of property, offer a nuanced understanding of the intricate valuation of various attributes within residential houses. The method uses real prices of property market and house attributes to estimate implicit prices for those attributes. Drawing from Freeman's insights (2003), these models dissect the contributions of structural, neighborhood, and environmental features to property values. Through this model, we identify the marginal implicit prices of attributes, indicating individuals' willingness to pay for slight alterations while keeping other factors constant. By analyzing real estate transactions, we aim to find the implicit prices of proximity to parks and green spaces from the total property price. Employing hedonic pricing, we aim to quantify these implicit prices, providing policymakers and urban planners with invaluable insights into the economic significance of safeguarding and augmenting urban green spaces.

Our objective is to assess the impact of proximity to green urban spaces on housing prices. A standard hedonic price function has the following form:

$$ln(p_{it}) = S_{it}\beta + N_{it}\gamma + E_{it}\delta + \epsilon_{it} \tag{1}$$

Where p_{it} represents the price of house i at time t, S_{it} is the vector of structural characteristics include variables such as the age of the house, the frame skeleton, and the area of the house. N_{it} is a vector of neighborhood characteristics. For instance, we used the distance from houses to the nearest metro station, school, and highway to show neighborhood characteristics. E_{it} is environmental characteristics which in this study is proximity to parks. We categorized parks based on their size, and then we measured the distance from houses to the nearest park. Also ϵ_{it} is an error term. We are mainly interested in δ which captures the average willingness to pay for proximity to parks.

The problem of model 1 is that the error term may contain unobserved neighborhood attributes that correlate with green space attributes like size and number and facilities they have. To overcome this problem, we adopt the fixed-effect approach. we use region fixed effects to circumvent the potential presence of omitted variables bias in the original model. These fixed effects can eliminate concerns related to time-invariant unobservable factors (geographical characteristics) and help identification come from within region variation. We also include time fixed effect to eliminates omitted variable bias caused by excluding unobserved variables that evolve over time but are constant across regions.

Another concern with model in Equation 1 is the potential bias and efficiency of estimates when the data is spatially dependent (i.e., data are spatially correlated; Polsky (2004); Schlenker et al. (2005); Chatzopoulos and Lippert (2016). According to the first law of geography, Tobler(1970), "everything is related to everything else, but near things are more related than distant things." As a result, spatial autocorrelation may occur; nearby observations may be more closely related than distant observations. Thus, we modify Equation 1 to let the model incorporate spatial effects. The rationales behind our modification are: First, the selling price of houses at any region act as a signal to guide other sellers to adjust their selling price due to their neighbors behavior. Second, the selling price of a house might depend on the characteristics of the houses close to that.

In the literature accounting for spatial dependency is generally through spatial models. If $Z_t = \begin{bmatrix} N_t \\ E_t \end{bmatrix}$, the General Nesting Spatial Model (GNS) is defined as (Anselin(1988); Elhorst(2014)):

$$P_t = \rho W P_t + \gamma S_t + W S_t \theta + \delta Z_t + \alpha + u_t, \qquad u_t = \lambda W u_t + \epsilon_t \tag{2}$$

Where W is the weighting matrix and ρ, θ, and λ are scalar parameters that show the strength of spatial dependence accounting for global spillovers, local spillovers, and spatially correlated error terms. ϵ_t is identically and independently distributed error terms with zero mean and variance σ^2 and α is the fixed effect. Equation 2 incorporates all spatial effects, but it may suffer from the problem of overfitting and identification problem Elhorst(2014). We set $\rho = 0$ but $\theta \neq 0$ to capture the local spillover effects which means in housing market the first order neighbor's housing characteristics may affect housing price. Setting $\lambda \neq 0$, commonly referred to as the spatial error model (SEM) if other spatial parameters are zero, is effective in capturing exogenous shocks not being observed by explanatory variables in the model (Kopczewska (2020)). The downside of SEM specification is that it fails to account for spatial spillover effects, which may lead to a misspecified model.

And finally, we will use Equation 3 for our analysis:

$$\begin{aligned} ln(p_{it}) = S_{it}\beta + W S_{it}\theta + N_{it}\gamma + E_{it}\delta \ + TimeFE + RegionFE \\ + TimeFE * RegionFE + \epsilon_{it} \end{aligned} \tag{3}$$

Due to the large number of observations in our study (more than one million), creating a weight matrix to link house i price to its neighbors characteristics is hard to achieve; as a result, an alternative approach is proposed. The average structural characteristics of all houses within the same region (commomn6- digit postal code) are used instead of forming a weight matrix. To reduce the influence of time on house prices, we consider houses traded in the same season and year along with spatial similarity.

We also control for spatial and temporal fixed effects with the equation.in Equation 3, "region FE" is a dummy variable that equals the urban district of the sample, and "Time FE" denotes the season and the year of the transaction. The marginal value of each attribute is estimated using Ordinary Least Squares (OLS) regression analysis. The estimation regression uses the natural logarithm of the house price per square meter as the dependent variable. For further investigation, we use the difference in differences method to find a causal relationship between the park opening and house prices.

2.2 Difference in Differences

Difference in differences method is one of the main methods of identification in econometrics. In fact, in the realm of identification, we seek a causal effect of explanatory variables that is exogenous and does not have endogeneity with unobserved factors. Endogeneity in this context may stem from the exclusion of relevant variables that could impact housing prices and exhibit correlation with the proximity to park variable. The presence of an omitted variable poses the risk of introducing bias and inconsistency into our analysis, underscoring the importance of addressing this potential source of error for a more robust and reliable assessment.

In adherence to the principles of a natural experiment, we undertake the essential step of categorizing the sample population into two distinct groups: the treatment group and the control group. In this experimental design, the intervention exclusively influences the treatment group, while other external factors concurrently impact both the treatment and control groups in a comparable manner. Thus, to discern the net effect of a natural experiment, it suffices to scrutinize the disparity between the outcomes of these two categories.

In our specific context, we designate houses situated within a distance less than 400 meters from a park as the treatment group. In contrast, the houses located between 400 meters and 1500 meters from the park constitute the control group. This strategic division allows us to evaluate and isolate the impact of proximity to metro stations on housing dynamics, providing a rigorous basis for analysis and interpretation.

$$Treatment = \begin{cases} 1 & \textit{in 400 m radius} \\ 0 & \textit{between 400 m and 1500 m} \end{cases}$$

We assume houses within closer radial ranges to the newly constructed park should receive more significant effects on their price. Therefore, the treatment group includes houses within a close radial range to the newly established parks and the control group includes the houses out of the specific radial. The following model is estimated to figure out the causal effect of opening a new park on housing price:

$$\ln P_{it} = \beta_0 + \beta_X X_{it} + \beta_p post_{it} + \beta_{tr} treat_{it} + \beta_{ptr} post.treat_{it} + \epsilon_{it} \tag{4}$$

In Equation 4, p_{it} represents the price of house i at time t, $post_{it}$ is series of Dummy variables indicating the time period after the park opening. For instance, it takes values 0 and 1, and it is defined to determine the transaction time of each traded property as a dummy variable. If the transaction time is after the opening, its value is set to 1, and if the transaction time is before the opening, it takes 0.

$$Post = \begin{cases} 1 & \textit{3 years after parks' construction} \\ 0 & \textit{3 years before parks' construction} \end{cases}$$

Moreover, $treat_{it}$ also is a dummy variable, which contains 0 and 1. The variable refers to the distance to the newly constructed parks. If the traded house is in the neighborhood of parks, the variable equals to 1, and on the other hand, it equals to 0.
X_{it} is other control variables that were introduced in previous sections. Moreover, $post.treat_{it}$ is The interaction term of $treat_{it}$ and $post_{it}$. In the above equation, β_{ptr} is the difference in differences coefficient of interest, which indicates the effect of the opening of the new park on its neighboring properties relative to the farther properties.

3 Data

In this research, we use a data set based on transactions of residential properties in Tehran, the capital city of Iran. Tehran serves as a vital hub of cultural, economic, and political activity. With a population exceeding 9 million inhabitants, Tehran ranks among the most populous cities in Western Asia. Spanning an area of approximately 730 square kilometers, Tehran is divided into 22 districts, each characterized by its unique socioeconomic and demographic profile. You can observe districts and urban green spaces of Tehran in Figure 1; numbers in polygons demonstrate name of urban districts.

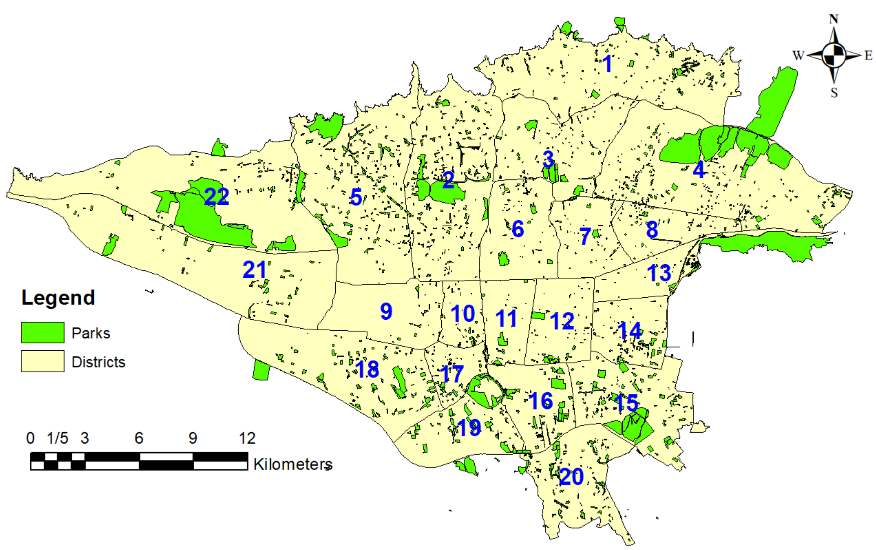


Figure 1: Tehran parks and districts

Additionally, we collect data on location and opening time of parks and metro stations in Tehran. We also utilized GIS, including Google Earth software, Google Maps, and urban maps provided by the Tehran Municipality, to delineate the cartography of the parks. Further analyses for obtaining the mentioned distances were conducted using ArcMap software. The distance is referred to as the Euclidean distance, representing the straight-line distance between residential structures and the boundary of the parks. The following subsections provide a detailed explanation of each data set.

3.1 Housing Prices

Data on house transactions is based on the recorded transactions by the Ministry of Roads and Urban Development. The dataset spans from March 21, 2010 to the end of 2018. Considering the specific research focus, we only examined the transactions of "residential apartments" in Tehran during this time period. This data set includes the following statistical information:

1. Transaction code
2. Date of Transaction
3. Total price of the house
4. Price per square meter
5. Area of the house
6. Age of the house
7. Type of building frame skeleton
8. Percentage of the property traded
9. 10-digit postal code of the house
10. District where each house is located

As noted earlier, this study exclusively focuses on residential apartments. However, districts 19 and 20 of Tehran only account for less than 0.2% of the total transactions, which leads us to exclude them from our data set. We also removed transactions with incomplete data and observations with identical transaction codes. Moreover, over 30,000 samples have postal codes that did not match their urban district. Consequently, we eliminate these observations. Approximately 1.5% of the total data consisted of transactions in which the entire house was not involved, and these were subsequently excluded. After implementing the previously mentioned exclusions, outliers comprising one percent of the data at each extreme, determined by "area" and "house prices in each district in each season," are removed from the sample. Moreover, we had to remove another portion of the data. In each region where the postal code at the 6- digit level is the same, and for each season of each year, if only one house had been sold, that observation should be omitted from the data set. We do that to correct spatial autocorrelation, calculating the average structural characteristics of all houses within the same region (commomn6- digit postal code) according to their transactions season and year. The total number of observations became 1,099,488 and the summary statistics of the variables are shown in Table 1.

Table 1: Summary statistics of residential properties

Variables	No. Obs.	Mean	Std. dev.	Min	Max
Price per square meter (Mill. Tomans)	1099488	3.97	2.95	0.08	54.81
AdjustedPrice (Mill. Tomans)	1099488	36.65	18.65	1.48	276.64
Age	1099488	8.60	8.42	0	49
Area (square meter)	1099488	83.72	36.84	35.38	380

Comments: "Adjustedprice" is adjusted price per square meter with housing inflation to the winter of 2022 (Source: Statistical Center of Iran).

3.2 Postal Code and Geographic Coordinates

Similar to various regions across Iran, postal codes in Tehran are constructed with 10 digits. Tehran's postal code system further divides the city into 1873 and 15016 segments at the 5-digit and 6-digit levels, respectively. Figures 2 and 3 depict polygons generated by the first five digits of the postal code. Although each house's postal code is 10 digits, the absence of specific geographic coordinates for each code prevents individual consideration. Consequently, Tehran is delineated into regions at the 6-digit level, assuming uniform geographic coordinates for all properties within a given region. This data is sourced from the National Post Office of Iran.

Figure 2 displays the average house price for all houses used in our study in each of the 5-digit regions; the prices are adjusted by the house inflation data obtained from the statistical center of Iran to the winter of 2022. In addition, Figure 3 represents the number of transactions in each of the 5-digit regions during the study.

3.3 Urban Green Spaces

In 2010, Tehran boasted approximately 1630 parks, a number that surged to over 2150 by 2018 (excluding districts 19 and 20, the numbers are 1450 and 1950, respectively). These parks exhibit significant diversity, ranging from the smallest at 129 square meters to expansive parks covering more than a hectare. Oversight of these green spaces falls under the purview of the Tehran Parks and

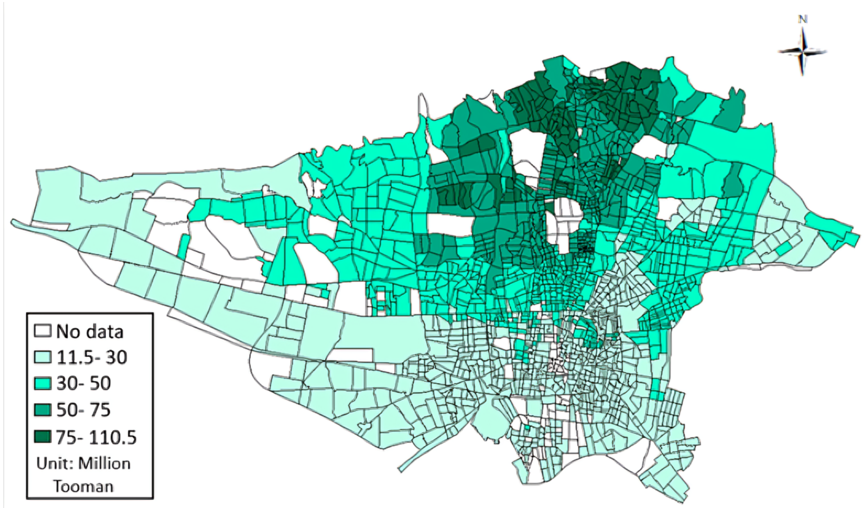


Figure 2: Average adjusted house prices: 2010-2018

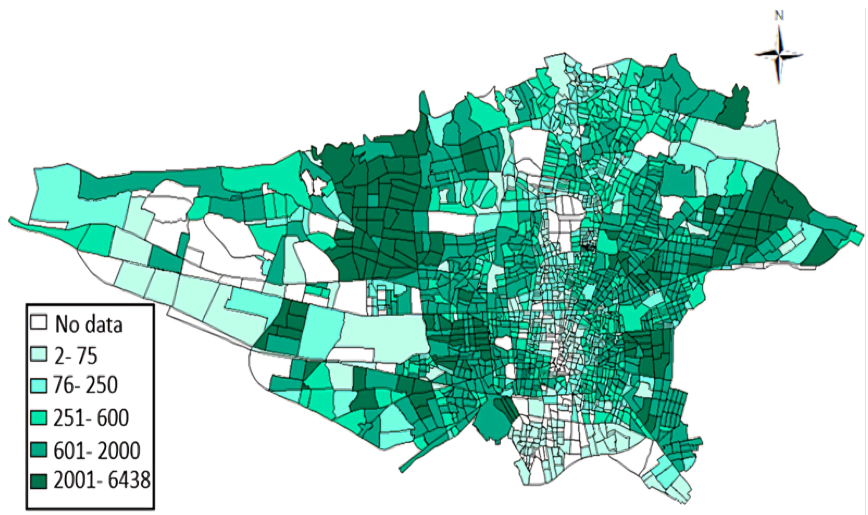


Figure 3: Number of transactions

Green Spaces Organization, responsible for collecting data on these areas. The acquired dataset encompasses the following variables:

1. Name of the parks
2. Area (size)
3. Year of opening

4. Park address
5. District

Accurately calculating the distance between houses and parks necessitates the use of geographic coordinates. To achieve this, we employed Google Earth software, Google Maps, and urban maps from the Tehran municipality. The parks' map was meticulously crafted using these tools, while further analyses to determine distances were conducted in ArcMap software. The calculated distance, known as the Euclidean distance, represents the straight-line distance from houses to the parks' boundaries. It's crucial to note that this mapping approach introduces a level of approximation to the research. However, with the resources at hand, we have strived to provide the parks map with the least possible error. To mitigate any potential inaccuracies, houses within 5 meters of the nearest park are conservatively considered to be precisely 5 meters distant. Given the potential for variations in effect based on size, we classified the parks as in Table 2:

Table 2: Classification of urban green spaces

Type	Explanation	No. of parks-March 2010	No. of parks-end of 2018	Average distance(m)
1- Very small	Smaller than $2550\,m^2$	552	801	416
2- Small	Between $2550\,m^2$ and $10200\,m^2$	649	824	408
3- Midsize	Between $10200\,m^2$ and $25500\,m^2$	258	319	709
4- Large	Between $25500\,m^2$ and $102000\,m^2$	127	155	1220
5- Very large	Greater than $102000\,m^2$	38	51	2063
Total	All the parks	1624	2150	218

Additionally, it must be noted that forest parks were excluded from this study. The total number of parks per urban district at the end of 2018 is illustrated in Figure 4. District 4, with 253 parks, has the highest number, while district 9, with 27 parks, has the lowest number. Furthermore, in Figure 5, you can observe the share of urban green spaces area in each district to the area of the district at March 2018. The numbers within the polygons represent the name of that urban district. For instance, parks in district 2 cover about 9.5% to 16.9% of the area of this district. Forest parks are excluded in both Figures.

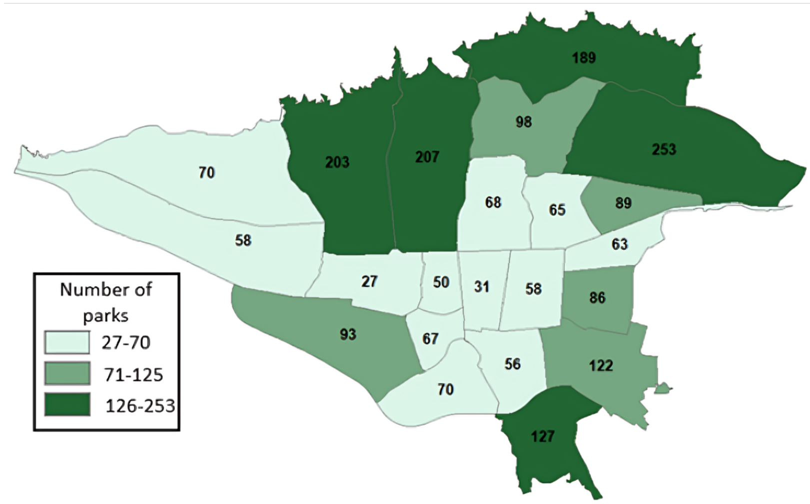


Figure 4: number of parks

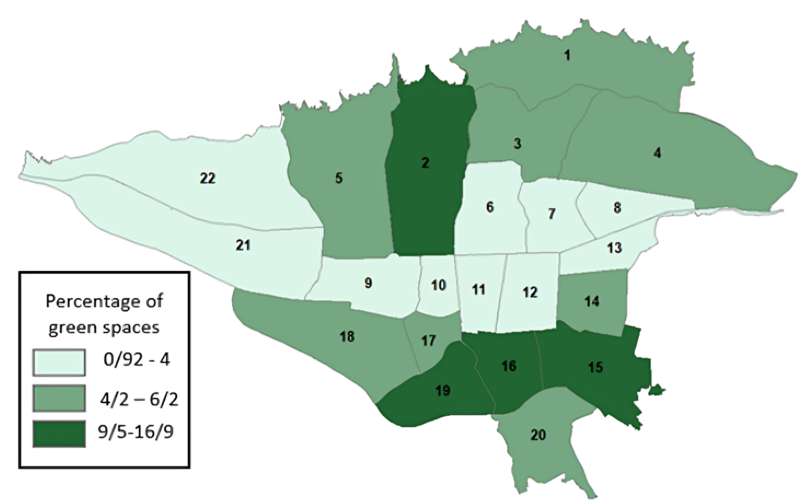


Figure 5: Share of green spaces to district area

3.4 Metro Stations

In our analysis, we include the distance to the metro station as a control variable to adjust for various factors that might influence housing prices. This consideration is particularly crucial as proximity to the metro not only facilitates convenient transportation but also bears significant advantages that can impact housing prices positively. Living close to a metro station often enhances accessibility, reduces commuting time, and contributes to a heightened sense of connectivity within the urban infrastructure. Moreover, the accessibility to public transportation can elevate the overall appeal of a neighborhood, potentially influencing housing prices upward due to increased demand for properties in such well-connected areas. The data related to metro stations has been obtained from the Tehran Metro Operation Company and includes the following information:

1. Name of metro station
2. Geographic coordinates
3. Date of the inauguration

Although the inauguration dates of metro stations are recorded on a daily basis, we assume that they affect the housing market before their official inauguration due to public awareness of their construction before they become operational. Therefore, we consider the timing of station inauguration on a biannual basis according to the Solar Hijri calendar. Moreover, we posit that the effects of a 100-meter variation in distance to the nearest metro station differ when we consider 200 to 300 meters instead of 1000 to 1100 meters. Consequently, we classified the distance to the nearest metro stations into two groups, as indicated in Table 3. We apply Euclidean distance and use 400 meters as a threshold as it indicates a walking distance neighborhood (Hu et al. (2019)), about 5-minute walking distance. The metro variables consisted of "DisMetro," "DisMetrogroup," and their interaction term. Using an interaction variable in this way, where the variables are the same nature, enhances the correlation between the variables, which increases the standard error of the related coefficients.

Table 3: Classification of Distance to Metro

Variable	Name of subgroup	Classification method
Metrogroup	group 1	less than 400 m
	group 2	more than 400 m

3.5 Other Data

We extend our investigation to include the proximity to schools and highways, recognizing the impact these elements can have on the housing market. Being close to schools is often associated with enhanced educational opportunities, making neighborhoods more appealing to families and potentially contributing to an increase in housing demand and prices. Similarly, proximity to highways can offer convenient commuting options, potentially influencing housing prices due to improved accessibility and connectivity.

It's important to note that while these proximity factors can positively influence housing prices, the potential negatives, such as increased crowd and noise levels, should also be considered, as they may have an adverse impact on the housing market dynamics. We employ the shapefile to determine the minimum distance from houses to highways as a neighborhood variable in our analysis. The shapefile of the highways is from the OpenStreetMap website, a comprehensive and freely accessible map covering the entire globe. Similar to our approach in assessing the distance to metro stations, we employ a dummy variable to represent the proximity of houses to schools. we posit that the effects of a 100-meter variation in distance to the nearest school differ when we consider 100 to 200 meters instead of 900 to 1000 meters because of the students' noise pollution. Therefore, we categorize distance to the nearest school according to Table 4. Our analyses only include The distance from schools as a dummy variable.

Table 4: Classification of Distance to School

Variable	Name of subgroup	Classification method
Schoolgroup	group 1	less than 300 m
	group 2	more than 300 m

Eventually, we calculate the distances from houses to the nearest park. We examine two distinct scenarios regarding the distances from houses to parks. In the first scenario, we compute the distance between houses and their nearest park and use it as a continuous variable. In the second scenario, parks are classified into five groups based on their size, and the estimation incorporates the distance from houses to each of these five park groups. These distance variables are used as continuous variables in our regression analysis. Table 2 details the classification. The names and descriptions of the main variables are listed in Table 5. Note that the variable "logprice" is the dependent variable:

Table 5: Variable definition

Variable Name	Explanation
logprice	natural logarithm of the house prices per square meter
DisParks	distance to the nearest park
DisPark1	distance to the nearest park of type 1
DisPark2	distance to the nearest park of type 2
DisPark3	distance to the nearest park of type 3
DisPark4	distance to the nearest park of type 4
DisPark5	distance to the nearest park of type 5
DisMetro	distance to the nearest metro station
Schoolgroup	dummy variable for distance to the nearest school

4 Results

4.1 Hedonic Pricing Method

In our initial modeling step, we establish the base model utilizing a single environmental variable—the distance to the nearest park. As mentioned earlier, our dependent variable is the natural logarithm of house prices per square meter. Detailed outcomes of this estimation are outlined in Table 6. Specifically, column (II) in the table addresses spatial autocorrelation by incorporating the average characteristics of nearby homes. In both columns, the "DisParks" coefficient consistently demonstrates a negative value, suggesting that, on average, house prices tend to decrease as the distance to the park increases. It's noteworthy that the coefficient for "DisParks" in the second column is statistically insignificant. In addition, the results of the control variables are in line with

Table 6: Impact of proximity to park on house prices

Indep. Vars	Logprice (I)	logprice(II)
DisParks	-0.0000170***	-0.00000238
	(0.000)	(0.276)
DisMetro	-0.000104***	-0.000127***
	(0.000)	(0.000)
Metrogroup = 2	-0.00776	-0.0170***
	(0.098)	(0.000)
DisMetro *	0.0000962***	0.000119***
Metrogroup = 2	(0.000)	(0.000)
Age	-0.0216***	-0.0251***
	(0.000)	(0.000)
Agesquare	0.000345***	0.000418***
	(0.000)	(0.000)
Schoolgroup	0.0270***	0.0201***
	(0.000)	(0.000)
$\bar{S}$	No	Yes
frame type	Yes	Yes
district FE	Yes	Yes
time FE	Yes	Yes
district FE * time FE	Yes	Yes
Area	Yes	Yes
Areasquare	Yes	Yes
Exp. Way	Yes	Yes
N	1099488	1099488
R-sq	0.759	0.774

p-values in parentheses $*p < 0.05, **p < 0.01, ***p < 0.001$

expectations. The effects of distance to the metro stations follow the logic based on which the “DisMetro” variable was categorized. For houses located within the initial 400 meters of metro stations, every meter of distance has a greater impact on housing prices. Moreover, houses located further than 300 meters from schools tend to be 2% to 2.7% more expensive than those in closer proximity, likely due to reduced noise pollution and congestion typically associated with school areas. Since we have formulated the equations in a semi-logarithmic form, the interpretation of coefficients is not linear. For example, in column (I), 200-meter change in distance to the nearest park change the house price by 0.34%.

Given the prevailing inflationary trends in the housing market, it is prudent to analyze our results across different periods as people’s housing preferences may evolve with the rise in prices. As depicted in Figure 6, we categorize our study into three distinct time intervals: In essence, we categorize the study period into three groups: the years 2010 and 2011, the years 2012 to 2016, and lastly, the years 2017 and 2018. The reason behind is that in 2012, there was a notable increase in housing prices, leading us to group the years 2010 and 2011 together. Subsequently, considering the stability in prices during the following years, they constitute another group. Finally, the years 2017 and 2018, characterized by a price surge, form the third group.

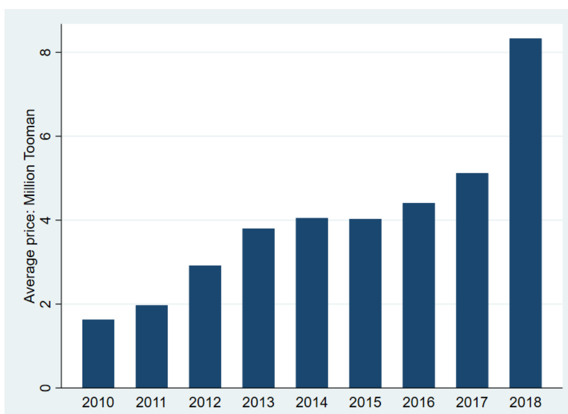


Figure 6: Average price by year

Results presented in Table 7 reveals a noteworthy trend: over time, and primarily influenced by housing inflation, the perceived value of green spaces by households diminishes. Notably, in the years 2010 and 2011, a shorter distance to the park corresponded to increased house prices; however, this assertion doesn’t hold true in the subsequent two time periods. Despite the positive coefficient associated with the distance to the park, its impact is neither economically nor statistically significant during these periods. To put it into perspective, in 2010 and 2011, holding all other factors constant, a hypothetical scenario involving two identical houses—one positioned 300 meters closer to the nearest park—indicates that the house in closer proximity to the park is approximately 1.23% more expensive than its counterpart.

Similar to the result of Table 6, the control variables are in line with our expectations. Impacts of distance to the metro stations is greater for houses located within the initial 400 meters of them, and houses located further than 300 meters from schools are 1.7% to 2.5% more expensive than closer ones.

Table 7: Impact of proximity to park on house prices- Temporal variation

	Logprice (2010- 2018)	Logprice (2010, 2011)	logprice (2012- 2016)	Logprice (2017, 2018)
DisParks	-0.00000238	-0.0000408***	0.00000650*	0.00000636
	(0.276)	(0.000)	(0.026)	(0.083)
Age	-0.0251***	-0.0283***	-0.0246***	-0.0257***
	(0.000)	(0.000)	(0.000)	(0.000)
Agesquare	0.000418***	0.000444***	0.000440***	0.000425***
	(0.000)	(0.000)	(0.000)	(0.000)
DisMetro	-0.000127***	-0.000108**	-0.0000967***	-0.000177***
	(0.000)	(0.008)	(0.000)	(0.000)
MetroGroup = 2	-0.0170***	-0.00821	-0.00794	-0.0322***
	(0.000)	(0.472)	(0.222)	(0.000)
DisMetro * (MetroGroup=2)	0.000119***	0.000102**	0.0000873***	0.000170***
	(0.000)	(0.008)	(0.000)	(0.000)
Schoolgroup	0.0201***	0.0173***	0.0192***	0.0245***
	(0.000)	(0.000)	(0.000)	(0.000)
N	1099488	237074	601462	251952
R-sq	0.773	0.463	0.630	0.792

p-values in parentheses $*p < 0.05, **p < 0.01, ***p < 0.001$

Another factor that can be influential is the classification of regions based on the residents' wealth. The stratification of regions according to residents' wealth emerges as a significant factor influencing housing prices. By considering the economic demographics of neighborhoods, we seek to unravel the nuanced preferences and priorities of diverse homebuyers.

Additionally, residents' wealth can be indicative of various amenities, services, and overall neighborhood desirability, all of which contribute to the complex interplay affecting housing values. For instance, rich neighborhoods may be associated with higher-end amenities, better infrastructure, and a more desirable living environment, factors that often contribute to an increase in housing prices. On the other hand, regions with a more diverse economic demographic may prioritize different aspects, such as proximity to educational institutions, public spaces, or cultural amenities. Understanding these dynamics allows us to appreciate how residents' wealth, reflected in the classification of regions, influences the demand for specific features like high-quality parks. This knowledge is vital for policymakers and real estate stakeholders to create tailored strategies that align with the preferences and priorities of diverse homebuyers, ultimately contributing to the sustainable development and attractiveness of different urban areas.

Our classification involved dividing urban districts in Tehran into two distinct groups—those deemed rich and those less affluent. Each group comprises six districts, representing the highest and lowest average housing prices, respectively. Recognizing the potential for disparate decision-making between these two groups, we have incorporated this categorization into our research. As anticipated, District 1 in Tehran emerges as the most expensive urban district. It's important to note that Figure 7 encapsulates the entire study period spanning from 2010 to 2018, with prices adjusted to reflect the winter of 2022.

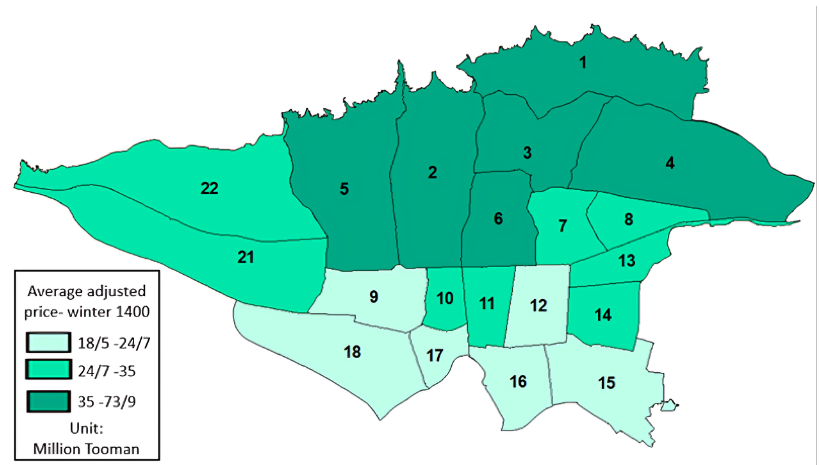


Figure 7: Adjusted average price by district

The results of this classification are presented in Table 8. The coefficient of DisParks is negative for rich regions, and its magnitude is greater compared to when the regression includes all of Tehran. This suggests that homebuyers in these rich regions are willing to allocate more financial resources for the proximity to parks, indicating that parks can be regarded as a luxury amenity. This observation aligns with the findings of the Laszkiewicz et al. (2019) study, which established that individuals' willingness to pay for park proximity escalates alongside increasing apartment prices. This implies that for certain buyers, residing near these well-maintained parks is considered a luxury, reinforcing the notion that such green spaces hold a premium value in the housing market.

In contrast, the coefficient of DisParks for less affluent regions exhibits a positive value. On average, housing prices in these regions tend to decrease as proximity to parks increases. The characteristics of parks in these areas may offer an explanation. As highlighted in the Introduction, parks come with both advantages and disadvantages, with one significant drawback being the potential for criminal activities in the vicinity, such as drug dealing. Parks in less affluent regions may be perceived as less secure, particularly during late hours, leading to associated issues like increased risks of robbery. It appears that parks in less affluent regions might be more prone to such problems, further influenc-

Table 8: Impact of proximity to park on house prices- Spatial variation

Indep. Vars	Logprice Tehran	Logprice Rich	Logprice Less affluent
DisParks	-0.00000238	-0.000121***	0.000170***
	(0.276)	(0.000)	(0.000)
Age	-0.0251***	-0.0248***	-0.0235***
	(0.000)	(0.000)	(0.000)
Agesquare	0.000418***	0.000426***	0.000350***
	(0.000)	(0.000)	(0.000)
DisMetro	-0.000127***	-0.000236***	-0.0000503
	(0.000)	(0.000)	(0.127)
MetroGroup==2	-0.0170***	-0.00457	0.0206*
	(0.000)	(0.597)	(0.043)
DisMetro *	0.000119***	0.000234***	0.0000130
(MetroGroup==2)	(0.000)	(0.000)	(0.694)
Schoolgroup	0.0201***	0.0207***	0.0144***
	(0.000)	(0.000)	(0.000)
N	1099488	519826	204837
R-sq	0.773	0.746	0.637

p-values in parentheses * p<0.05, ** p<0.01, *** p<0.001

ing the housing market dynamics in these areas. Furthermore, it is noteworthy that the perceived value of access to metro stations is comparatively lower in less affluent regions than in rich ones. For instance, a 200-meter difference in distance to the nearest metro stations within the first 400 meters, increase house prices by 4.72% in rich regions, and 1% in less affluent ones. This disparity may be attributed to the higher concentration of metro stations in these less affluent areas. This observation aligns with the findings of YazdaniFard et al. (2019), which indicated a positive effect ranging from 2 to 11 percent for new metro stations in regions with limited existing public transport infrastructure. In contrast, regions with an already extensive public transportation system exhibited a less than 2 percent positive effect. Table 9 presents the ratio of metro stations in less affluent to rich regions, considering their area.

Table 9: Number of metro stations

	Regions area	No. metro stations at the end of 2009	No. metro stations at the end of 2018
Rich regions	258 km^2	22	61
Less affluent regions	119 km^2	20	36
The ratio of metro stations in less affluent to rich regions, considering their area		1.97	1.28

In this segment, we delve into the dynamics of rich and less affluent regions during the periods 2010-11 and 2017-18, aiming to discern the evolving impact of parks on housing prices over time. As illustrated in Table 10, there is a noticeable shift in the coefficients: in rich regions, the magnitude has decreased, whereas in less affluent regions, it has witnessed an increase (highlighted by the negative coefficient of "DisParks" in the first row for rich regions and a positive one for less affluent regions). In essence, this suggests that the adverse effects of parks on housing prices have intensified in both rich and less affluent regions. This aligns with the presumption that environmental amenities, particularly access to parks, are increasingly perceived as luxury goods.

Moreover, an examination of the statistical significance of coefficients in both rich and less affluent regions reveals a noteworthy distinction. While the adverse effects of parks on housing prices have intensified over time in rich regions, these changes lack statistical significance. In contrast, the alterations observed in less affluent regions are deemed statistically significant. These variations can be attributed to the factors previously discussed. Economic conditions have deteriorated over time, relating to an increase in crime rates. Parks, as potential settings for such activities, consequently experience heightened negative effects on their surroundings. Furthermore, it is posited that the rise in crime is more pronounced in less affluent regions, contributing significantly to the observed changes in coefficients within these areas.

Table 10: Impact of proximity to park on house prices- spatiotemporal variation

Indep. Vars	Logprice Rich	Logprice Less affluent
DisParks	-0.000142***	0.000118***
	(0.000)	(0.000)
year = 2017-18	2.002***	1.735***
	(0.000)	(0.000)
DisParks * year = 2017-18	0.0000227	0.0000845***
	(0.451)	(0.000)
DisMetro	-0.000209**	-0.000137
	(0.002)	(0.070)
Metrogroup = 2	-0.00597	-0.0200
	(0.075)	(0.382)
DisMetro * Metrogroup = 2	0.000207**	0.000102
	(0.002)	(0.178)
N	240868	80747
R-sq	0.839	0.796

p-values in parentheses * p<0.05, ** p<0.01, *** p<0.001

In the following tables, we investigate a different model than the previous ones to examine the claim we discussed earlier. Suppose our claim about the unsafe space of parks in less affluent regions is correct. In that case, we will expect more negative effects of larger parks on the housing prices in their neighborhood because larger parks may be more likely to experience criminal activities than smaller ones. Consequently, we eliminate the "DisParks" variable, which represents the distance from the nearest park, and instead, we use five other variables named "DisPark1", "DisPark2", "DisPark3", "DisPark4", and "DisPark5". The number at the end of their names indicates the type of park in their classification based on their size; a greater number indicates the larger size of parks (refer to Table 2). The results obtained from regressions for the years 2010 to 2018, with the categorization of rich and less affluent regions, are presented in Table 11.

Table 11: Impact of proximity to each type of park on house prices

Indep. Vars	Logprice Tehran	Logprice Rich	Logprice Less affluent
DisPark1	-0.00000503*	-0.00000235	0.000000961
	(0.035)	(0.528)	(0.810)
DisPark2	0.0000174***	-0.0000150***	-0.0000197***
	(0.000)	(0.001)	(0.000)
DisPark3	0.0000260***	-0.0000330***	0.0000879***
	(0.000)	(0.000)	(0.000)
DisPark4	-0.0000438***	-0.0000606***	0.0000782***
	(0.000)	(0.000)	(0.000)
DisPark5	-0.00000204**	-0.0000237***	0.0000122***
	(0.004)	(0.000)	(0.000)
N	1099488	519826	204837
R-sq	0.775	0.751	0.648

p-values in parentheses * $p<0.05$, ** $p<0.01$, *** $p<0.001$

As one can see in Table 11, in less affluent regions, proximity to parks of type 1 exhibits no negative effect on house prices, and for parks of type 2, the effect is positive. However, this trend reverses for larger parks, exceeding 10,200 square meters, where proximity results in a decrease in house prices. Conversely, in rich regions, proximity to any of the five park types does not lead to a price decrease. On average, parks larger than 2550 square meters even contribute to an increase in the prices of nearby houses. These findings underscore the evolving nature of people's preferences for green space over time. To gain a comprehensive understanding of how individuals in different areas navigate housing inflation amidst shifting green space preferences, it is advisable to explore various temporal and spatial combinations within the dataset.

Over time, people's value of green spaces is expected to decrease in all regions. Table 12, which pertains to rich regions, shows that the coefficients of distance to parks in 2010-11 indicate the greatest value; that is, during a period when prices had not yet risen significantly (relative to the study period), people attached the highest value to proximity to green spaces. For example, from the coefficient of "DisPark1", we find that they positively affected on house prices only in this period. Comparing the distance to parks in these two periods shows that the first price shock in 2012 did not significantly affect people's choices regarding green spaces, maybe due to the price stability during 2014-16. However, looking at the last two years of the study, people's preferences have changed, and their willingness to pay for green spaces has decreased. Similarly, we expect that conditions will worsen in the years after 2018, and the impact of parks on house prices will decrease.

Table 12: Impact of proximity to each type of park on house prices- Rich regions

	Logprice (2010- 2018)	Logprice (2010- 2011)	logprice (2012-2016)	Logprice (2017- 2018)
DisPark1	-0.00000235	-0.0000277***	0.00000399	0.00000741
	(0.528)	(0.000)	(0.438)	(0.329)
DisPark2	-0.0000150***	-0.0000293**	-0.00000541	-0.0000235**
	(0.001)	(0.002)	(0.387)	(0.007)
DisPark3	-0.0000330***	-0.0000325***	-0.0000385***	-0.0000225***
	(0.000)	(0.000)	(0.000)	(0.000)
DisPark4	-0.0000606***	-0.0000652***	-0.0000585***	-0.0000616***
	(0.000)	(0.000)	(0.000)	(0.000)
DisPark5	-0.0000237***	-0.0000259***	-0.0000231***	-0.0000243***
	(0.000)	(0.000)	(0.000)	(0.000)
N	519826	116327	278958	124541
R-sq	0.751	0.357	0.506	0.736

p-values in parentheses * $p<0.05$, ** $p<0.01$, *** $p<0.001$

The findings from Table 12 highlight a distinct scenario in rich regions where two identical houses are considered, differing only in their proximity to parks of type 3. Specifically, a 400-meter distance between these houses results in a 1.3% change in house prices during the years 2010 and 2011. However, it's noteworthy that the impact of the same 400-meter difference to the park decreases to 0.9% in the subsequent years of 2017 and 2018. This suggests a notable shift in the significance of park proximity on house prices over the specified time periods.

Furthermore, from Table 13, we find that in less affluent regions, proximity to parks type 1 and 2 had a positive effect on house prices in the years 2010 and

2011. People in these regions were willing to pay for proximity to smaller parks. Additionally, larger parks have a negative impact on housing prices, and people tend to avoid having their homes close to these parks. As we mentioned earlier, it is because of the disadvantages of parks, specifically criminal activities.

Table 13: Impact of proximity to each type of park- Less affluent regions

	Logprice (2010- 2018)	Logprice (2010- 2011)	logprice (2012- 2016)	Logprice (2017- 2018)
DisPark1	0.000000961	-0.0000202*	0.00000498	0.0000217*
	(0.810)	(0.011)	(0.341)	(0.017)
DisPark2	-0.0000197***	-0.0000260**	-0.0000290***	0.0000401***
	(0.000)	(0.002)	(0.023)	(0.000)
DisPark3	0.0000879***	0.000106***	0.000106***	0.0000139
	(0.000)	(0.000)	(0.000)	(0.061)
DisPark4	0.0000782***	0.0000209***	0.0000864***	0.000101***
	(0.000)	(0.001)	(0.000)	(0.000)
DisPark5	0.0000122***	-0.00000276	0.00000304	0.0000800***
	(0.000)	(0.350)	(0.159)	(0.000)
N	204837	40811	124090	39936
R-sq	0.648	0.250	0.376	0.625

p-values in parentheses * $p<0.05$, ** $p<0.01$, *** $p<0.001$

The coefficients for distance to different types of parks in rich and less affluent regions can be explained by referring to Figure 8 and Table 14. Small parks are more prevalent in rich regions; conversely, large parks are more accessible in less affluent regions. Therefore, in rich regions, proximity to larger parks positively impacts house prices more than small parks. This means that in addition to the differences in parks' effects on the local community, another influencing factor on house prices is the abundance of each type of park: fewer parks, greater impact. Indeed, Table 14 confirms the trends observed in Figure 8. It indicates that the average distance from houses to parks Type 1 and 2 in less affluent regions is greater than in rich regions, which could account for the value of smaller parks in these areas; the opposite is true for larger parks.

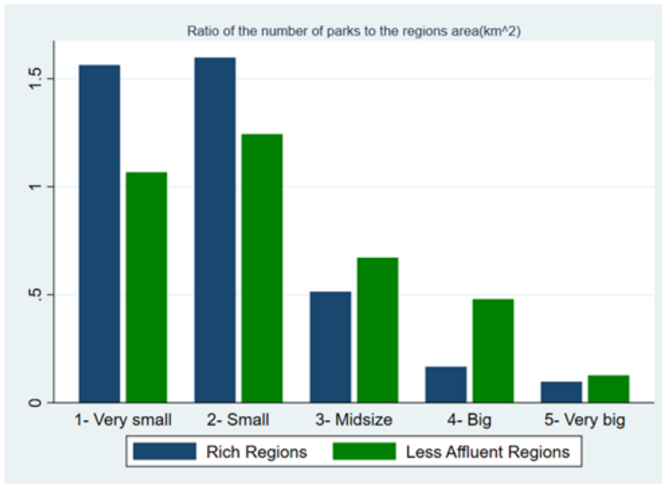


Figure 8: Ratio of number of parks to the districts' area

Table 14: Park variables in rich and less affluent regions

	Rich		Less affluent	
Vars	Average	Std. error	Average	Std. error
DisParks	197.89	136.38	233.21	150.94
DisPark1	423.08	317.58	469.10	337.89
DisPark2	342.40	236.83	494.26	333.69
DisPark3	689.43	533.83	703.02	498.58
DisPark4	1190.54	816.18	1009.83	715.22
DisPark5	1639.72	918.78	1289.87	932.53

4.2 Difference in Differences

4.2.1 Empirical Result

Based on the results obtained from the Hedonic Pricing method, we found that the midsize parks had a significant impact on house prices. In addition, this type of park contains parks from 10000 to 25000 meter square, which means their size are not totally different than each other, and we can consider it as a homogeneous treatment.

In contrast with this type of parks, parks from type 1, and 2 are very small to impact the surrounding properties significantly. Moreover, for the bigger parks, we know that their construction is a time consuming activity, and in more projects they built in several phases in different years. Therefore, it violates no anticipation assumption of difference in differences.

We consider the construction of midsize parks as an exogenous policy. Since we do not know the exact timing of parks' construction, we assume that they were built in the first January of each year, or at least people were aware of them before their official opening and had adjusted their expectations with the park's construction.

At the first, we should get familiar with our study area. from Table 15, we find more than 50% of midsize park constructed in rich regions that is a sign for spatial variation. Moreover, the table shows a time variation in parks' construction in different regions. most of midsize park in rich regions were constructed in the first half of our study, and for the less affluent regions it seems different. Regarding these spatiotemporal variation, I'm concerned about the analysis of the entire city of Tehran as a unit. Therefore, like our analysis in previous section, we split Tehran into rich and less affluent regions.

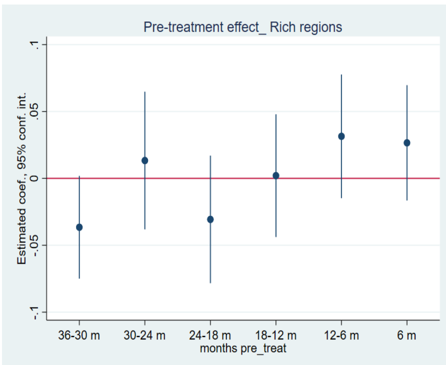
Table 15: number of constructed midsize park

Year	Tehran*	Rich	Less Affluent
2011	6	6	0
2012	10	5	3
2013	11	5	0
2014	8	5	3
2015	5	2	3
2016	2	1	1
2017	5	2	2
2018	1	1	0
Total	48	27	12

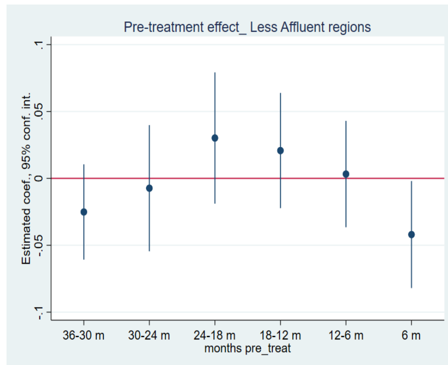
* Districts 19, and 20 have been excluded

As we mentioned earlier, treatment group contains houses in 400 meters radius from new parks boundaries, and the control group contains the traded houses between the treatment buffer and the radius of 1500 meters. In this framework, we consider 3 years before, and 3 years after the treatment to create our subsample; the first group is pre_treatment, and latter forms post_treatment. For more clarification, if a park was constructed in 2014, our subsample contains all the houses in 1500 meters radius of the park, which were traded from 2011 to 2013 (pre), and 2014 to 2016 (post).

The results are presented in Table 16; before examining the results, it is important to note the similarity in the price trend of control and treatment groups. We utilize our DiD specification on the part of a sample which includes only the houses that their post variable equals to 0, or the pre_treatment subsample. Therefore, our sample only consisted of 3 years before the parks' construction. In addition, we categorized these 3 years into 6 months basis, and plot the interaction term of these time periods and treat. As shown in figure **??**, prior to the parks' construction, the coefficient of the interaction term is not significant, which means the price of control group and treatment group did not go to different trend.



(a) Rich regions



(b) Less affluent regions

Columns (I),and (II) are related to the rich regions, and column (III),and (IV) show the result of less affluent regions. As shown in Table 16, being in the treatment group in rich regions leads to a 2.9 percent increase in house prices while the impact of new midsize parks in less affluent regions is reverse, and it decreases the treated properties prices more than 3.5%. These different net impacts belongs to the characteristics of these regions; where in less affluent regions, parks are potential cite for criminal activities. In addition, the magnitude of coefficients has been lowered when we consider the treatment at the radius of 500 meters.

Table 16: Result of difference in differences

	Rich Regions		Less Affluent Regions	
	400 m	500 m	400 m	500 m
1.post	0.0521***	0.0568***	-0.0568***	0.0528***
	(0.000)	(0.000)	(0.000)	(0.000)
1.Treat	-0.0529***	-0.0419***	-0.0142***	-0.0138***
	(0.000)	(0.000)	(0.009)	(0.002)
1.post#1.Treat	0.0289***	0.0190***	-0.0357***	-0.0279***
	(0.000)	(0.001)	(0.000)	(0.000)
N	110376	110258	62959	62959
R^2	0.663	0.663	0.618	0.618

p-values in parentheses $*p < 0.05, **p < 0.01, ***p < 0.001$

4.2.2 Robustness Check

From the previous table, we found that the impacts of parks are greater in their proximity in both regions. In addition, we apply different methods for the definition of post variable to check our result one more time. According to Table 17, we introduce post variable in two different ways: 2 years and all years. like our base framework, that we define post variable in 3 years after and before the time of treatment, we just change these years to 2 and all years after, and before the treatment.

Table 17: Definition of Post Variable

post variable	2 years	all years
0	2 years before treat	all years before treat
1	2 years after treat	all years after treat

The result of these analysis are shown in Table 18, where the impacts of new midsize parks' construction in rich regions are positive in both method, and also they are greater in 400 meters radius than the 500 meters, which aligns with our previous estimations. From the table, we see the house prices in 400 meters radius can increase between 1.9% to 3.7%.

Table 18: Robustness Check- Different method

	Rich Regions				Less Affluent Regions			
	2 years		all years		2 years		all years	
	400 m	500 m	400 m	500 m	400 m	500 m	400 m	500 m
1.post	0.0325***	0.0344***	0.0323***	0.0314***	-0.0109*	-0.00857	-0.164***	-0.161***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.085)	(0.169)	(0.000)	(0.000)
1.Treat	-0.0394***	-0.0270***	-0.0764***	-0.0592***	-0.0259***	-0.0189***	0.0102**	-0.00681*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.024)	(0.070)
1.post#1.Treat	0.0190***	0.00661	0.0373***	0.0153***	-0.0224***	-0.0144***	-0.0598***	-0.0391***
	(0.014)	(0.318)	(0.000)	(0.002)	(0.008)	(0.037)	(0.000)	(0.000)
N	85411	85409	181219	180765	48340	48340	94008	94005
R^2	0.678	0.678	0.741	0.741	0.630	0.630	0.642	0.642

p-values in parentheses $*p < 0.05, **p < 0.01, ***p < 0.001$

Moreover, in Less Affluent regions, we observe that the midsize parks decreases their surrounding house prices between 2.2 to 6 percent, and their impacts are more intense in smaller radius. In both regions, we can see the coefficient of interest variable in "3 years" method is greater than "2 years", and for the "all years" is bigger than the others. These finding show that parks influence their surrounding properties even in long time. To check this claim, we can do another analysis.

In this framework, we want to measure dynamic impacts of the parks construction. Therefore, we need another definition for post variable. Lets consider n as the result of "time of trade" minus "time of park's construction", then:

$$n = time\ of\ trade - time\ of\ treat$$

$$post = \begin{cases} 0 & n < 0 \\ n+1 & n \geq 0 \end{cases}$$

Houses that were traded before the park construction get the amount of 0, and for the houses that were traded after construction, they gwt different amount greater than 0. For instance, if a house has been traded 5 year after the park's construction, its post variable equals to 6. Result of these analysis are shown in

Table 19: Dynamic Effects

	Rich Regions		Less Affluent Regions	
	400 m	500 m	400 m	500 m
1.Treat	-0.0741***	-0.0548***	0.00962**	-0.00653*
	(0.000)	(0.000)	(0.032)	(0.081)
1.post#1.Treat	0.0208**	0.0177**	-0.0774***	-0.0466***
	(0.020)	(0.021)	(0.000)	(0.000)
2.post#1.Treat	0.0597***	0.0344***	-0.0790***	-0.0571***
	(0.000)	(0.000)	(0.000)	(0.000)
3.post#1.Treat	0.0270***	0.00615	-0.0477***	-0.0498***
	(0.002)	(0.447)	(0.000)	(0.000)
4.post#1.Treat	0.0322***	0.00934	-0.0762***	-0.0522***
	(0.000)	(0.183)	(0.000)	(0.000)
5.post#1.Treat	0.0391***	0.00250	-0.0747***	-0.0503***
	(0.000)	(0.736)	(0.000)	(0.000)
6.post#1.Treat	0.0611***	0.0197***	-0.113***	-0.110***
	(0.000)	(0.005)	(0.000)	(0.000)
7.post#1.Treat	0.0705***	0.0427***	-0.125***	-0.105***
	(0.000)	(0.000)	(0.000)	(0.000)
8.post#1.Treat	0.0460***	0.0402***		
	(0.000)	(0.000)		
N	181219	180765	94008	94005
R^2	0.742	0.742	0.651	0.651

p-values in parentheses $*p < 0.05, **p < 0.01, ***p < 0.001$

Table 19. As we expected, the midsize parks' construction has positive impacts in rich regions, and its impacts become bigger during the time. The table shows construction of new parks can increase house prices between 2 to 7 % in 400 meters radius. Moreover, for less affluent regions, we fond a falling trend in close house prices; after 6 years, the price decreases by 10% in these regions.

5 Conclusions

Urban green spaces bring about substantial benefits, contributing to improved local air quality and providing recreational opportunities for communities. Nevertheless, these spaces may present challenges, with a potential rise in crime rates being one of them. In our study, we employ both the hedonic pricing method and the difference in differences approach to thoroughly investigate the economic implications of urban green spaces on housing prices in Tehran, the capital of Iran.

The hedonic pricing method estimates housing prices as a function of housing characteristics, neighborhood, and environmental variables. We demonstrate that the impact of green spaces on housing prices is not uniform but varies significantly depending on the area and the location of the properties. Residents in rich regions are willing to spend more to be close to parks, indicating a higher valuation of these environmental amenities. However, this relationship reverses in less affluent regions, where proximity to green spaces, except small ones, leads to lower house prices. Additionally, the housing market inflation decreases the general willingness to pay for proximity to green spaces across all regions.

We also investigate our results based on the size of the parks. We divide the parks into five categories according to their size, and the results show that in rich regions, proximity to parks of all sizes generally enhances property values, particularly for larger parks. Over time, this positive effect on property prices shows a declining trend, as indicated by the reduced influence on prices in later years. In contrast, less affluent regions exhibit a varied response, with smaller parks positively affecting house prices, while larger parks, often associated with negative factors like criminal activities, decrease property values, with this negative effect intensifying over time. The disparity in park types and their prevalence across regions also influences these trends, where the scarcity of a certain type of parks in an area augmenting its impact on housing prices.

Furthermore, we employ the difference in differences method to delve deeper into estimating the causal effects of proximity to parks on housing prices. Specifically, we focus on the construction of midsize park. we utilize multiple framework to check the robustness of our result. The results unveil that the construction of a midsize park in rich regions led to an average increase of 2% to 4% in the prices of neighboring houses during that period, showcasing the premium placed on such amenities at the time. Moreover, for the less affluent regions, we fond that parks net effects are negative, and they reduce neighborhood house prices about 2.5% to 6%.

These discoveries emphasize the intricate interplay between economic factors and the perceived value of green spaces within urban landscapes. The nuanced relationship unveiled in our study underscores the necessity for thoughtful urban planning and policy formulation. To truly meet the diverse needs and economic contexts of different communities, it is imperative to craft strategies that go beyond a one-size-fits-all approach. Implementing targeted policies, grounded in a deep understanding of the varied preferences and economic realities of distinct neighborhoods, will foster sustainable and equitable urban development. This approach not only enhances the quality of life for residents but also contributes to the overall well-being and vibrancy of our urban environments.

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