Which size for urban green parks? French evidence of the rental market

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Abstract

Faced with increasing urbanisation and the climate crisis, the development of green spaces in cities has become a major issue for urban planners. While the benefits of having housing close to green spaces have been widely established in the literature, the question of the size to allocate to the latter becomes crucial in a context of intense land-use pressure. This paper explores this question, in the case of France, by leveraging databases of the local rent observatories for rental prices and OpenStreetMap for parks. Using a generalised propensity score weighting method, it uncovers the preferences between different typologies of park sizes in the private rental market of the largest French urban areas in 2017 and 2018. The results show that, on average, individuals value large parks more, followed by small and lastly by medium-sized parks. There are variations in this hierarchy of preference depending on flat size and its location. These findings are of interest not only to property investors looking to increase their rental income, but also to political decision-makers looking to improve existing parks and propose new urban park development projects.

Keywords: Urban green spaces; Hedonic pricing; Environmental amenities; Housing rental market

JEL Classification: Q26; Q51; R14; R31

1 Introduction

With rising living standards, increasing urbanisation and the environmental crisis, the question of green spaces has become a central issue in public policy. According to a survey conducted by UNEP-IFOP in 2016, 85% of French people consider the proximity of a green space to be an important criterion in their choice of residence[1]. Nevertheless, these green spaces are unevenly distributed across the country. In cities, for example, their presence is scarcer than in rural areas and of different types. Even within cities, while some people only have to walk a few steps to reach the nearest park from their home, others must use transportation to access one.

To meet these growing needs, many policy planners are moving towards greener urban development, for example, by developing and redeveloping green spaces such as urban parks, which are major green spaces in towns and cities. However, setting up urban parks is difficult in these areas where the pressure for land use is strong. For public decision-maker, the creation of an urban park on vacant land may be perceived as less profitable than the creation of a commercial or residential area (Votsis, 2017). Yet, the literature has highlighted the strong positive externalities of urban parks in economic, health, social and environmental terms (see for review Jabbar et al. (2021)). Quantifying these externalities is therefore necessary to guide public decision-makers in land allocation decisions.

While the positive effect of proximity to a park on property prices has been widely demonstrated (Łaszkiewicz et al., 2019; Morancho, 2003; Wu & Dong, 2014), the question of the right size to allocate to these areas remains to be explored, particularly in a context of tension over land use (Haaland & van den Bosch, 2015). Indeed, depending on their size, parks do not offer the same types of use, services and visitor numbers. While some studies have shown that large parks offer more amenities (Giles-Corti et al., 2005; Hayward & Weitzer, 1984), the 'Just Green Enough' theory (Wolch et al., 2014) would stress that they could generate environmental gentrification and would recommend instead the establishment of small green spaces spread evenly over the area. The question of the size to be allocated to these parks is therefore of paramount importance.

The aim of this study is to reveal, via the property market, the preferences of individuals for the size of the parks in their vicinity. This work makes four contributions to the literature based on the challenges of hedonic models for environmental assessment identified by (Bishop et al., 2020). Firstly, while most hedonic studies on the valuation of green amenities are carried out at the scale of a city or urban area, I chose to extend the scale to the ten largest French urban areas to obtain results with better external validity. Secondly, data from the Observatoires Locaux des Loyers (Local Rent Observatories), which is still rarely used in the economic literature, make it possible to analyse the private rental market, whereas the vast majority of studies are based on property transactions (Palmquist, 2005). The use of rents provides a better reflection of amenity flows, also helps to limit the anticipation bias that is so prevalent in property sales prices, and is fairly relevant in this study area, i.e. the major urban areas,

[1] https://www.lesentreprisesdupaysage.fr/content/uploads/2019/12/unep-ifop-2016-villes-de-demain-20160321.pdf

where rental rates are fairly high. Thirdly, I contribute to the literature on the identification of urban parks both in terms of the data used and the indicator selected. On the data side, I identify parks using OpenStreetMap, a collaborative database combining fine resolution and large data coverage, which remains underutilized in economic literature on this subject. With regard to the selected indicator, while the majority of studies look at the value of parks by distance to parks, I choose to study a less explored dimension, park size. Furthermore, while the few studies that include this size indicator treat it as a continuous variable, I choose to discretize this variable to better reflect the perception of individuals. To do this, I conduct an in-depth review and analysis of park size classifications to propose the most consistent on my scale of study. Last but not least, I complement the traditional hedonic approach with causal inference using generalised propensity scores to limit certain selection biases linked to the non-random distribution of parks and dwellings in the area. This bias on the subject of economics valuation of green spaces in the real estate market was recently highlighted by Liu et al. (2024).

This study therefore identifies the type of park size that is most highly valued on the French rental market. I combine data on urban parks from the OpenstreetMap collaborative database with data from local rent observatories in the ten largest French urban areas (with the exception of Montpellier) in 2017 and 2018. After a broad review of the heterogeneity in park size classifications, I break down parks sizes into 3 main categories: small, medium and large. Using a generalised propensity score weighting based on the Covariate Balancing Propensity Score (CBPS) method, I assess the impact of a multivalued treatment, in this case the size category of the park closest to each dwelling, on the rent paid. I find, in decreasing order of preference, that individuals on the private rental market generally value large parks first, then small ones, and finally medium-sized parks. This order of preference, however, changes depending on the type of property and, in particular, its surface area, but also depending on the location of the property in relation to its centrality, its distance to the park or the degree of greenery nearby. These results offer interesting information for investment, planning and management decisions, whether for real estate investors or public policies in charge of these spaces.

The remainder of the paper is structured as follows. After a review of the literature in section 2, I present the data in section 3 as well as the empirical strategy in section 4. In section 5, I discuss the estimation results and in section 6, I provide overall conclusions.

2 Literature review

Over the last years, many studies have demonstrated the positive value that people place on urban green parks in the housing market (Crompton, 2001; 2005). Distance, as a proxy for accessibility, is the most commonly used variable to determine this impact. In general, there is a broad consensus in the literature on the negative relationship between the price of a dwelling and its distance to a green space (Łaszkiewicz et al., 2019; Morancho, 2003; Wu & Dong, 2014). Therefore, this result encourages the provision of green parks in cities. Implementing this type of recommendation remains a major challenge, however, given the pressure on land in certain areas, particularly in cities (Gavrilidis et al., 2022; Haaland & van den Bosch, 2015). Knowing that proximity to a green space is important, the policy maker faces an additional important trade-off: how much land should be allocated to the green space in order to achieve maximum benefits? To the best of my knowledge, few studies have attempted to determine the sizes of green space that maximise the property value of the surrounding housing. Lutzenhiser and Netusil (2001) show that the current sizes are less than optimal, and Picard and Tran (2021b) and Picard and Tran (2021a) demonstrates that these optimal sizes vary according to location. More precisely, according to these latter, the socially optimal share of land devoted to urban green spaces is a concave function of the distance from the CBD; it first increases and then decreases as one moves away from the CBD. This reflects the trade-off between high land values in the center, which make urban green space too expensive, and sparse population in the periphery, which associates urban green space with too few social benefits.

Indeed, the proximity approximated by the distance to the green space is not the only characteristic of a green space that is valued. The size, quality, shape, and density of this space can also influence the use that an individual makes of it and therefore the valuation that he or she places on it (Franco & Macdonald, 2018; Melichar & Kaprová, 2013; Wu & Dong, 2014). Compared to distance, size is much less used in studies as a measure of green space (Osland et al., 2020), but it is sometimes used in addition to distance and is often interpreted in interaction or at least in relation to it. Some authors justify this lesser use of the size metric by a lesser effect of this measure compared to distance (Franco & Macdonald, 2018; Morancho, 2003; Picard & Tran, 2021b). However, it is not uncommon for the effect of size to be stronger than that of distance when both metrics are incorporated into studies (Liebelt et al., 2018a; Poudyal et al., 2009).

To justify the use of this metric, various authors (Czembrowski & Kronenberg, 2016; Larson & Perrings, 2013; Liebelt et al., 2018a; Zambrano-Monserrate et al., 2021) point out that, depending on the size of the green space, the uses and services offered are not the same. Liebelt et al. (2018a), for example, point out that small urban green spaces usually have playgrounds and fields, while large parks may offer opportunities to hike and access to flora and fauna. Thus, agents' preferences for particular services and uses influence the valuation of green spaces according to their size. In terms of coverage, larger parks with more capacity can benefit more people, but are therefore more likely to generate noise and congestion (Anderson & West, 2006; Bolitzer & Netusil, 2000; Franco & Macdonald, 2018). Roberts et al. (2022) also emphasize the multiplicity of amenities offered by large parks, with features of direct use such as children's play areas and features of biodiversity. Additionally, from an environmental point of view, the effectiveness of the cool islands provided by green spaces improves with their size (Algretawee, 2022; Oliveira et al., 2011). Large green spaces also have better ecological quality by providing habitats for various species and improving diversity (Melichar & Kaprová, 2013). However, to avoid the phenomena of segregation, also known as green gentrification, some studies recommend giving priority to improving existing greenery and, above all, to implementing many small green spaces scattered throughout the cities rather than a few large parks (Franco & Macdonald, 2018; Wolch et al., 2014).

Moreover, unlike distance, there is no broad consensus on the sign of the effect of park size on real estate prices. Even if most studies using the size of the green space as a metric find a significant but weak positive impact on price (Bolitzer & Netusil, 2000; Chen et al., 2020; Czembrowski & Kronenberg, 2016; Franco & Macdonald, 2018; Larson & Perrings, 2013; Liebelt et al., 2018b; Poudyal et al., 2009; Tyrväinen, 1997), some studies find instead a negative coefficient (Anderson & West, 2006; Cho et al., 2008; Wu & Dong, 2014) and others a non-significant effect (Choumert & Travers, 2010; Morancho, 2003). The differences in results can be linked by different ways of integrating the size of the parks in the models according to the studies. While some studies integrate this continuously as the total area of the park, others (see Table A1 in Supplementary Material) include the size in a categorical way. Nevertheless, in this second case, the thresholds separating the different park size categories are far from universal as shown in Supplementary Material (Table A1). Of course, there are different ways of naming parks size categories, depending on the scale and context of the study. For example, a small park can also be called a "mini park", "pocket park" or "vest-park", a medium-sized park can also be called a "neighbourhood park" or "community park" and a large park can also be called an "urban park", "city park" or "district park" (see Table A1 in Supplementary Material). However, as the last column of Table A1 in Supplementary Material shows, their definition, use, and characteristics such as radius of attraction, levels of provision and type of activity practised are similar between the studies. Smaller parks are used by fewer people within a very close radius. They have few features and services and are used more for passive activity and social interaction (Kemperman & Timmermans, 2006; Peschardt et al., 2012; Rey Gozalo et al., 2019). Larger parks are visited by more people and from further away. They offer a wider choice of features, activities and vegetation (Figueroa et al., 2018; Giedych & Maksymiuk, 2017; Rey Gozalo et al., 2019; Sarı & Bayraktar, 2023). Compared with smaller parks, they are used more for physical activities (Brown et al., 2014; Rey Gozalo et al., 2019; Sarı & Bayraktar, 2023). Therefore, only the size threshold for differentiation between categories shows significant differences. While in some studies the difference between small and medium-sized parks is established at a threshold of 0.5 hectares (Breuste & Rahimi, 2015; Christian et al., 2017; De Luca et al., 2021), in other studies it is 5 hectares (Łaszkiewicz et al., 2019; Sadeghian & Vardanyan, 2015; Stark et al., 2014; Ummeh & Toshio, 2017), i.e. 4 times larger. Zhang and Han (2021), in a literature review of Chinese and English studies of pocket parks, find that it was only the size that differed between studies of this type of park.

Furthermore, the literature on the value of urban parks, regardless the indicator used (distance, size, etc.), shows heterogeneous preferences depending on the spatial context and the socio-demographic and economic characteristics of the population (Anderson & West, 2006; Liebelt et al., 2018b; Roberts et al., 2022; Saphores & Li, 2012; Xiao et al., 2016; Zhang et al., 2021). First, preferences differ according to the type of individual. Property status, i.e. whether they own or rent, and the type of dwelling they live in, i.e. house or apartment, influence their behavior and thus their preferences regarding amenities. Indeed, on the question of green space valuation, although the majority of studies in the literature have focused on on owners using sales data (Bishop et al., 2020), some studies find heterogeneous effects according to the property type and are still far from reaching a consensus on the sign associated with each type. Liebelt et al. (2018a), for example, find a positive and significant effect for house and flat rentals but not for sales. They justify this effect by the fact that, as rentals are generally more limited in time, individuals are less inclined to invest in individual green spaces than owners and, therefore, pay more attention to the environmental amenities surrounding the dwelling. Panduro and Veie (2013), on the other hand, find a significant and positive effect of park size on the sale price of houses but not on the sale price of flats. Moreover, studies have highlighted differences in the way parks are used and valued, depending on the household composition (single or with children), with families with children making greater use of parks (Kemperman & Timmermans, 2006; Zhao et al., 2024). Nevertheless, in contrast to contingent valuations, studies using hedonic models often have less access to information on individual characteristics. Dwelling characteristics can sometimes reflect the characteristics of the individuals living in them. For example, dwelling size can reflect household composition, as suggested by the study by Hoshino and Kuriyama (2010). By focusing on the value of green space in one-room dwellings, this study seeks to highlight the preferences of a specific population: young people, singles and/or low-income earners, rather than families. Several previous studies have shown that certain types of parks and green spaces are more highly valued in larger homes (Anderson & West, 2006; Liebelt et al., 2018b; Saphores & Li, 2012).

In terms of spatial context, differences in neighborhood structure, design and development can lead to varying valuations of parks. A conditional effect of proximity to the city center has been repeatedly identified (Brander & Koetse, 2011; Cho et al., 2008; Votsis, 2017). High population density in city centers, often combined with increased scarcity and congestion of green spaces, leads to greater value being placed on them. As a result, green spaces such as parks are particularly valued in dense urban environments. In addition, the degree of greenery and the presence of other environmental amenities can influence the degree to which parks are valued. Several studies in the literature have examined the question of substitutability and complementarity between different types of green space (Franco & Macdonald, 2018; Mansfield et al., 2005; Panduro & Veie, 2013; Shan et al., 2024). Trojanek et al. (2018) showed that the lack of greenery around buildings leads to a higher premium for public green spaces. Panduro and Veie (2013) as well as Woo and Webster (2014) suggest that some green area respectively private and clubs can serve as substitutes for public green spaces. Shan et al. (2024) goes even further, showing that green club spaces complement large parks but substitute for smaller ones. Finally, proximity to a park is an important factor to consider. While previous literature largely agrees on the real estate premium associated with proximity to a park, some studies qualify this result according to the size of the park. Indeed, proximity to large green spaces can have a negative impact on housing prices (Anderson & West, 2006; Franco & Macdonald, 2018; Hoshino & Kuriyama, 2010; Osland et al., 2020; Pandit et al., 2013; Poudyal et al., 2009; Wu & Dong, 2014; Xiao et al., 2016). Congestion and noise pollution, which are more pronounced near large green spaces, can offset the positive externalities of these spaces when they are too close to housing.

3 Data

3.1 Local Rent Observatories

This study uses an original and seldom-used database from Local Rent Observatories (LRO). This French network, which currently has 34 observatories located in France, was created at the instigation of the Ministry of Housing in 2013. The LROs collect data on housing in a relatively homogeneous way from individuals but also from professionals to ensure that the data is representative[2]. The scope of the study depends on the data from the local rent observatories. In fact, despite the many new observatories set up over the years, they do not cover all French towns or cities and the number of observations varies greatly from one observatory to another (Table 11).

In total, I have access to more than one million observations on housing between 2015 and 2019 from 26 LRO in nearly sixty urban areas (Table 11). Given the small number of single-family homes in the sample (about 6% of observations) and, to work on a relatively homogeneous market, I restrict my analysis to multi-family housing in metropolitan France.

Then, I proceed to geocoding the dwellings using their postal address to assign geographical variables to the dwelling according to their location. The geocoding is carried out using the "API Adresse"[3]. This API (Application Programming Interface) allows querying the National Address Database. The results of the geocoding are available in Table 1: almost 85% of the observations were accurately georeferenced at the level of the dwelling's mailbox, with a total failure rate of only 8.74%.

Table 1 Geocoding results

	Frequency	**% Total**	**% Total Cum.**
Housenumber	885,440	84.64	84.64
Locality	4,411	0.42	85.07
Municipality	26	0	85.07
Street	64,802	6.19	91.26
Failure	91,400	8.74	100
Total	1,046,079	100	100

Based on the INSEE classification, I restrict my analysis to the 10 urban areas (called "aire d'attraction urbaine" in French and noted AAV) with 700,000 inhabitants or more, with the exception of Montpellier, which is not available in the database. I only have data for each of these 10 urban areas for 2017 and 2018. I therefore limit my analysis to these two years. Finally, I exclude from the sample 16 dwellings for which the declared surface area is less than the legal threshold of 9 m^2.

[2]Details of the survey methodology : https://www.cohesion-territoires.gouv.fr/sites/default/files/2019-05/Comite%20scientifique%20de%20l%27observation%20des%20loyers_Prescriptions_methodologiques_mars_2018.pdf

[3]https://adresse.data.gouv.fr/api-doc/adresse

I extract from the LRO data, the dependent variable of the hedonic model, i.e. the amount of the monthly rent excluding charges. The LROs also provide the postal address of the dwellings, the year the property was surveyed as well as various structural characteristics of the dwelling, like the surface and the period of construction, which will be used as a control variable in the model.

In total, after these various treatments, the analysis is based on 467,182 dwellings. The average rent for this sample is 789€ and the average surface area is 54 m^2.

3.2 Green indicators with OpenStreetMap

To construct the treatment variable relative to park size, I use the collaborative database OpenStreetsMap (OSM). OSM, offers a source of detailed data on a very large scale, updated in real time. Thanks to this data, I can accurately identify urban parks, whereas traditional data sources such as Corine Land Cover, NDVI, or the Urban Atlas include all green spaces without distinction. Furthermore, with this data source I am able to capture even the smallest parks, whereas Corine Land Cover and the Urban Atlas are limited to areas of 25 hectares and 0.25 hectares, respectively. For example, as the smallest park in Paris measures 42 square meters, I can only analyse it using Open Street Map. Despite its many advantages, this source is still underutilized in economic studies of the value of green spaces, with only a few recent studies employing it (Piaggio, 2021; Schindler et al., 2018). Using OSM, I first detect parks and green spaces across the whole metropolitan France territory (see Appendix A for details). On this scale, there are no fewer than 85,152 listed parks with an average surface area of 1 hectare. Next, I identify the nearest park to each dwelling, as this is most often studied in the literature due to its high probability of use and its significant impact on real estate prices. In this way, I can assign each dwelling information on the minimum distance, size and perimeter of the nearest park.

In view of the research question, I am particularly interested in the variable concerning the size of the nearest park. As explained in section 2, park size is captured in the literature either by a continuous variable or with several dummies reflecting size categories such as small, medium or large parks. The use of a continuous size variable, used in several studies on the subject (Bolitzer & Netusil, 2000; Choumert & Travers, 2010; Morancho, 2003) and as initially extracted from OSM, does not seem the most suitable in this context to capture the preferences of individuals. Indeed, individuals are unlikely to know the size of the nearest park to the nearest hectare or square meter, and they are also unlikely to notice and modify their behaviour in the rental market following a small variation in the size of a park. However, individuals may have in mind the type of size of the park, i.e. whether it is small, medium or large. Depending on the size of the park, the services provided, the amenities on offer, and the number of visitors are not the same. I therefore transform the continuous variable of park size into a categorical variable reflecting the type of size. There is no official or harmonised classification of park sizes. In fact, the thresholds used to separate the different types of size, both in the literature and in the development plans of certain cities, vary widely, and the difference between the different classifications is sometimes extremely broad (see the column "Size criteria" in Supplementary Material, Table A1). There is almost no literature or public documentation on this subject in France or in some of these cities. More generally, the thresholds for categorising park sizes may differ according to the country and even between cities of a same country. If I simply base my choice on the ranking of the categories in ascending order without taking into account the thresholds, I nevertheless find similarities in the different uses made of these spaces in each category (see the column "Usage" in Supplementary Material, Table A1). For example, due to their small size, the categories referring to small parks are used by a smaller population and for more passive recreational activities than the large park size categories. Based on these definitions, as well as the case-by-case comparison of the parks detected by OSM and the park lists of certain municipalities in the sample, I establish the variable *T_multi* with the classification described in Table 2. Thus, 25.37% of the dwellings in the sample have a large park as their nearest park, 45.90% a medium park and 28.73% a small park.

Table 2 Classification of urban park sizes

T_multi	Size (hectare)	Definition
Small	<0.1	Small parks are generally compact urban green spaces used by the nearby local population. These are for informal play and passive recreation which sometimes include some seating and play equipment.
Medium	0.1-1	Medium-sized parks are larger than small parks and often offer a greater variety of facilities and amenities. They may include landscaped gardens, water features, sports fields, picnic areas and sometimes community events. Medium-sized parks are often frequented by residents from adjacent neighbourhoods.
Large	>1	Large parks are extensive green spaces, often offering a significant natural escape in an urban environment. They can be home to a variety of recreational, cultural and natural experiences such as walking trails, woodlands, conservation areas, lakes or rivers, wildlife corners, accrobranches or museums. Large parks are often popular destinations for local residents and visitors for outdoor and leisure activities.

3.3 Other control variables

To estimate the propensity score model and the outcome model, I control for various other confounding variables that influence both treatment and outcome. Table 3 describes these variables and Table 12 provides descriptive statistics.

First, at dwelling level, in addition to the collect year, the surface area and period of construction extracted from LRO databases, I create three other variables using the dwelling's GPS coordinates: *nearestpark_min*, *Greenness* and *DIST_TC*. As the literature has largely demonstrated the impact of distance from the nearest park on housing prices, I control this value using the variable *nearestpark_min*. Then, by extending the selection on OSM to include all green spaces, I calculate the green index in the vicinity of the dwelling as a control variable (*Greenness*). This index controls for the density of green space in the vicinity, defined as the sum of all green space areas within a 1 km radius of the dwelling. The 1 km threshold is chosen on the basis of the literature on how far people walk daily in their neighbourhood, and more specifically on the literature on green spaces (Choumert & Travers, 2010; Hu et al., 2022; Kolcsár et al., 2021; Liu et al., 2024; Zhang et al., 2020). This represents about 15-20 minutes of walking. Individuals can walk in their neighbourhood to access local services such as shops and schools if they are within this radius, and the degree of greenery will influence their perception and therefore price they are prepared to pay to live in this environment (Franco & Macdonald, 2018; Ishikawa & Fukushige, 2012). Neighbourhoods with little green space may therefore reflect a lack of investment by local politicians in this sector, and we can therefore imagine that the parks closest to housing in these neighbourhoods will be small. The variable $DIST\_TC$ controls the distance to the coastline. As the sea and ocean are also valued environmental amenities, their proximity may have an impact both on property prices (Landry & Hindsley, 2011; Prayaga, 2017) and on the size of nearby parks, as these blue spaces are also recreational areas that can be a substitute for parks (Fleischer & Tsur, 2003). Therefore, close to the sea or the ocean, it is possible that the parks will be smaller because these very large blue amenities already offer a much wider recreational area than any park.

On a slightly broader spatial scale, I control for the age of the housing stock at the IRIS[4] level, the centrality of the municipality in the urban area and, finally, the urban area to which it belongs. More specifically, $Part\_av46$ measures the proportion of the stock of homes in 2012 that were built before 1946 in the IRIS. This variable controls the degree of development and urbanisation at the end of the Second World War, a time when very little urban parks had yet been built. Thus, the more dwellings there were at that time, the smaller the size of the nearest park is likely to be, as land occupation is high. The $CATEAAV2020\_11$ variable is based on the INSEE classification of municipalities within the urban area. This classification captures the degree of centrality of the municipality within the urban area. I therefore create a dummy equal to 1 when the municipality of the dwelling is a municipality in the centre of the urban area. These municipalities are very dense and therefore there is strong land pressure, which influences the rent paid but also the size of the parks within it. Several studies show that parks in city centres are generally smaller in size (De Luca et al., 2021; Liu et al., 2022). Other indicators of locality and centrality were analysed for robustness (see Appendix C). Given the similarity of the results, I chose $CATEAAV2020\_11$ because it is the variable that best reduces heterogeneity between the control and treatment groups. Finally, I check the urban area to which each dwelling belongs with the variable noted $AAV2020$. This variable takes into account cultural differences and policies for the development of green spaces such as parks, but also the specific characteristics of the rental market in each urban area. Following recommendations of Bishop et al. (2020), I include this last variable in the models in interaction with the dummy variable on the years of collect to allow the price functions to differ in space and time.

[4] IRIS (Îlots Regroupés pour l'Information Statistique) is a geographical subdivision used in France to collect and analyse statistical data on a small scale, often associated with a specific neighbourhood or area.

Table 3 Description of variables

Variables	Description	Source	Scale
	Outcome		
rent	Monthly rent excluding charges at the date of the survey (€)	LRO	housing
	Treatment		
T_multi	Size categories of the nearest park: small (<0.1 ha), medium (0.1-1 ha), large (>1 ha)	OSM	housing
	Covariates		
collect_year	Year the dwelling was surveyed: 2017 or 2018	LRO	housing
surface[1]	Living space of the dwelling (in m^2)	LRO	housing
surface2[1]	The variable "surface" squared	LRO	housing
n_epco5	Period of construction of the dwelling: 1 = before 1946, 2 = 1946-1970, 3 = 1971-1990, 4 = 1991-2005, 5 = after 2005	LRO	housing
nearestpark_min[1]	Distance to nearest park edge (meters)	OSM	housing
Greenness[1]	Area of parks within 1 km radius of dwelling (hectares)	OSM	housing
DIST_TC	Distance to coastline (meters)	HISTOLITT®, IGN	housing
Part_av46	Share of housing built before 1946 (%)	RP, Insee	IRIS
CATEAAV2020_11	Dummy variable: 1 if central municipality, 0 otherwise	INSEE	Municipality
AAV2020	City urban area in 2020: 001 = Paris, 002 = Lyon, 003 = Marseille, 004 = Lille, 005 = Toulouse, 006 = Bordeaux, 008 = Nantes, 010 = Strasbourg, 013 = Rennes, 014 = Grenoble	INSEE	Urban Area

[1] These variables are used in logarithmic form in the models.

4 Identification strategy: The generalized propensity score approach

The aim is to estimate the causal effect of park size on rents breaking down park size into 3 main categories: small, medium, and large parks. The identification method is based on the generalized propensity score approach (Imbens, 2000; Lechner, 2001).

Formally, I consider a set of N housing, indexed by $i = 1, ..., N$. For each sample unit i, I observe the triplet $(Y_i; T_i; X_i)$ where $Y_i = Y_i(T_i)$ is the actual outcome corresponding to the actual treatment received (outcome variable), T_i is the actual treatment received (multivalued treatment variable) and X_i is a vector of covariates (e.g., flat surface, green density around, period of construction...). In this study context, the treatment corresponds to size category of the nearest urban park and the outcome refers to the rent paid. The multivalued treatment variable, T_i with

$T \in \{0, 1, ..., K\}$, can take 3 values : "small" (T_i=0), "medium" ($T_i = 1$) and "large" ($T_i = 2$).

Thus I note $D_t(T_i)$ as an indicator denoting the receipt of treatment t for individual i :

$$D_{ij}(T_i) = \begin{cases} 1, & \text{if } T_i = j \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

For each observation i, there is also a set of potential outcomes $Y_i(t)$ with a given level of treatment. It is the potential outcome of household i under treatment level $t \in T$, where T ={0,1,2}. Given that there is only one nearest park for each home, only one of the potential outcomes is observed.

Hence, these potential outcome can be used to define pairwise treatment effects. The treatment effects at an individual level for treatment level m compared to treatment level l (the control group) is established as $Y_{im} - Y_{il}$, which is the difference between these potential outcomes. Consequently, it can be inferred at the population level by calculating average effects. At this level, two types of indicator are calculated in the literature, the Average Treatment Effect (ATE) calculated on the entire population and the Average Treatment Effect on the Treated (ATT) on the sub-group that received the treatment of interest:

$$ATE^{ml} = E\left[Y_{im} - Y_{il}\right] \tag{2}$$

$$ATT^{ml} = E\left[Y_{im} - Y_{il} \mid T_i = m\right] \tag{3}$$

As this study is intended to provide support for public policy, I estimate the ATT for the various possible treatment pairs. However, this study is not an experimental framework, as the treatment is not randomly assigned. The size and location of the parks depend on historical factors and urban planning, among other things. Furthermore, the price differences observed could be influenced by factors other than the size of the parks, such as the attributes of the housing or the socio-economic, demographic, and geographical characteristics of the neighbourhood.

To account for potential endogeneity and selection bias, statistical methods based on the propensity score are widely used (Austin, 2011; Rosenbaum & Rubin, 1983). The propensity score (PS) adjustment method proposed by Rosenbaum and Rubin (1983) is one of the most widely used approaches for causal inference. It aims to explain the variation in an outcome variable between treated units and non-treated counterfactuals. However, at the beginning, this method only applies to binary processing. Nevertheless, in many cases the treatment is multivalued or continuous, such as an amount of money, different types of medication or fertilizer. Subsequently, the literature has extended the propensity score methods to the cases of multivalued treatments (Imbens, 2000; Lechner, 2001) and, more recently, to continuous treatments (Hirano & Imbens, 2004; Imai & van Dyk, 2004). The approach of Imbens (2000), also called "generelized propensity score" (GPS), is particularly suitable for this study with multivalued treatment variable as urban park size categories. Thus, in this paper, I estimate the outcome (i.e. the level of monthly rent) that is associated to specific treatment category (i.e. the category of park size). In the following, the GPS method is briefly recalled as described in Imbens (2000) and adjusted to this case.

The implementation of this approach consists of three steps. The first step is the estimation of the propensity score. Since the treatment is multinomial, I estimate a generalised propensity score (GPS) using a multinomial logistic regression. It is defined as the conditional probability of receiving a particular level of the treatment given the covariates and can be formulated as follows:

$$r(t,x) \equiv \Pr(T = t \mid X = x) = E[D(t) \mid X = x] \tag{4}$$

Similarly to the propensity score with binary treatments, the generalized propensity score is assumed to have a balancing property which requires that, within strata $r(t,x)$, the probability that $T = t$ does not depend on the value of X. In other words, conditionally on observable characteristics X, when looking at two housing with the same ex-ante probability of having a certain level of treatment, their actual level of treatment is independent of housing observable characteristics, with the propensity score summarizing all the information so that:

$$D(t) \perp X \mid r(t,X), \forall t \in \mathcal{T}. \tag{5}$$

In the second step, treatment-specific predicted outcomes for each subject are derived from an outcome model estimated using regression weighted by GPS and then potential outcome mean for each treatment level are calculated:

$$E\left[\frac{Y \cdot D(t)}{r(T,X)}\right] = E[Y(t)] \tag{6}$$

Finally, in the third and last step, treatment effect indicators, like the ATT in this case, can be estimated by taking the mean difference of the potential outcome means obtained previously in the target population.

There are different methods and estimators possible to estimate the ATT using a generalized propensity score approach. I use the weighting method called "Covariate Balancing Propensity Score"[5] (CBPS) developed by Imai and Ratkovic (2014). They have shown that this method can greatly improve the performance of standard propensity score weighting by improving robustness to model misspecification through optimisation of the balance of covariates between treatment groups. Moreover, I include covariates in the outcome model and make the effect estimate "doubly robust". The double robustness property means that even if one of the two models (propensity score or conditional outcome model) is misspecified, the estimation of causal effects remains valid and consistent as long as the other model is correctly specified. The variables used for the specification of propensity score model and the outcome model are detailed in Table 3.

[5]I use the R package "WeightIt" (https://cran.r-project.org/web/packages/WeightIt/index.html) to implement this process.

5 Findings

5.1 Baseline and sensitivity analysis

Figure 1 as well as Table 13 allow examining the quality of the balancing achieved by the weighting method. In the case of a binary treatment, the graph shows the absolute difference between the treated and untreated groups for each covariate. Here, in the case of a multi-level treatment, this graph displays for each covariate the absolute difference for the pair of treatment groups with the greatest difference. Once the weighting has been applied, all maximum differences are below the 0.1 threshold recommended by Stuart et al. (2013). Thus, weighting by propensity score allowed reducing the differences between the different treatment groups on the covariates selected in this study.

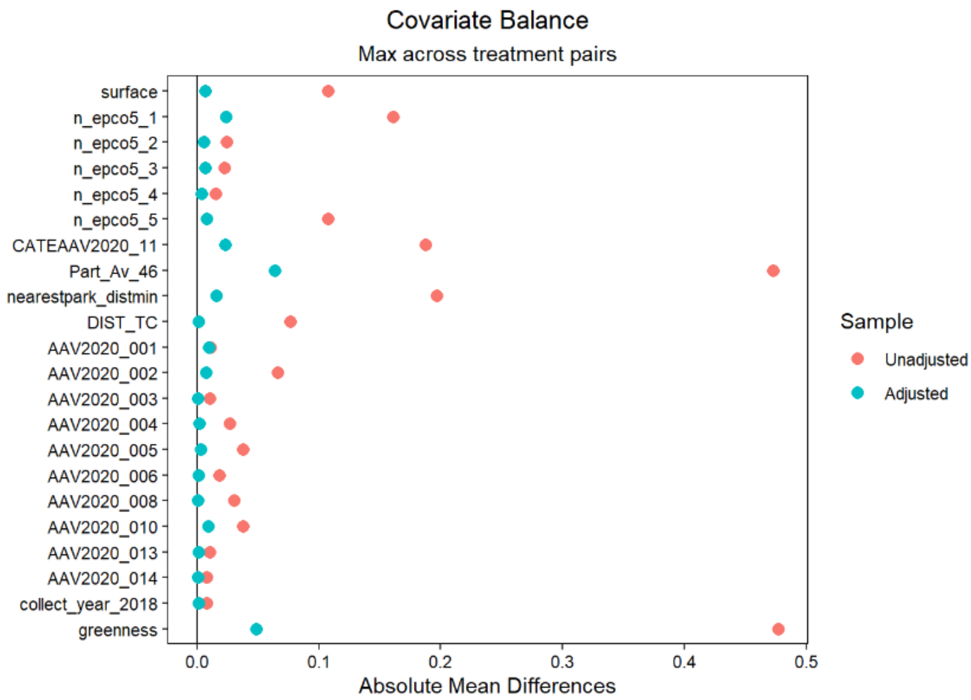

Fig. 1 Graph of covariate balance before (unadjusted) and after (adjusted) weighting variables using the propensity score model

Table 4 presents the average treatment effect on treated (ATT) obtained using the doubly robust CBPS weighting estimator. First, the significance of all the coefficients follows the literature according to which the size of the nearest park influences the rent of nearby flats. Therefore, tenants in large French urban area consider the urban park in the vicinity of their homes when choosing where to live. More specifically, all other things being equal, the rent paid differs according to the size of the nearby park. Tenants living near a small-sized park pay an average monthly rent of 8.82€ less than a tenant living near a large-sized park. On the other hand, they pay on average a monthly rent 13.23€ more expensive than tenants living near a medium-sized park. These price differences illustrate different preferences depending on the size of the nearest park. Therefore, in descending order of preference, people prefer first large-sized, then small-sized parks and finally medium-sized nearby parks. This nonlinear result differs from previous results in the literature. These differences in preference can be explained by different uses and attendance depending on the size of the parks. The size of urban park for which individuals are willing to pay the most, which I therefore set at the size the most valued by individuals, is large parks. This result is similar to the literature and is largely explained by the great diversity of services, features and amenities offered by them (Brown et al., 2014; Roberts et al., 2022; Ummeh & Toshio, 2017). In terms of physical activity for adults, they allow long walks, running or cycling. They generally offer a variety of specific activities such as an animal corner, an acrobranch, or a body of water (Ummeh & Toshio, 2017; Wright Wendel et al., 2012). They have activities for children as well as quieter places for adults. Their large size makes it easier to cut themselves off from the noise and pollution of the city. On the environmental side, they host a greater diversity of fauna and flora (Rey Gozalo et al., 2019; Ummeh & Toshio, 2017) and offer a greater capacity for freshness.

Table 4 Multi-valued treatment effects on rent

	Baseline	**Entropy**	**Optweight**
Medium *versus* Large	-22.05***	-24.1***	-15.67***
	(1.17)	(1.18)	(1.16)
Small *versus* Large	-8.82***	-11.1***	-5.79***
	(1.17)	(1.29)	(1.30)
Small *versus* Medium	13.23***	13.0***	9.88***
	(1.15)	(1.13)	(1.11)
N	467,182	467,182	467,182
- *Small*	134,223	134,223	134,223
- *Medium*	214,450	214,450	214,450
- *Large*	118,509	118,509	118,509

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Robust standard errors in parentheses.

Secondly, while articles including a continuous park size variable often find a real estate price increasing with the size of the park, I find a non-linear effect using discrete classes in size. Individuals prefer and value small parks more than medium-sized parks. Indeed, individuals pay on average a monthly rent of 13.23€ more to be close to a small park compared to a medium park. These differences in preference can also be explained by different uses and attendance depending on the size of the parks. At first sight, this in-between size might seem better for the individual, as it improves on some of the disadvantages of smaller parks, in particular by offering more space and therefore more places for different activities. However, it may not be large enough to benefit from all the advantages of large parks and therefore retains some of the disadvantages of small parks. First, this larger park may attract more people than a small park (Cohen et al., 2010; Zhang & Zhou, 2018), but because it is not as big as a large park, overcrowding and congestion may be felt more than in large parks (Franco & Macdonald, 2018; Liu et al., 2022). Indeed, medium-sized parks are less likely to have parking to limit congestion than large parks (Ummeh & Toshio, 2017). In addition, a feeling of insecurity is more likely to emerge from this type of size compared with small and large parks. Social interactions may be weaker than in small parks because there are more people and therefore more strangers coming from further away, and therefore, no people known in the neighbourhood of the place of residence (Vos, 2005). In addition to this, this type of park also combines several factors that favor insecurity. For example, people perceive medium-sized parks to have less light and more graffiti than larger parks (Ayala-Azcárraga et al., 2019), elements that reinforce crime in parks as well as the feeling of insecurity (McCord & Houser, 2017; Tower & Groff, 2016). They are also generally less well maintained, monitored and are more often open and accessible, even at night, than larger parks (Wright Wendel et al., 2012). Larger than small parks, they have more vegetation (Wright Wendel et al., 2012) and therefore more nooks and crannies to hide illicit activities than small parks (Mak & Jim, 2018). Finally, Massoni et al. (2018) state that small-scale parks can be substituted for medium-scale parks because they cover almost the same diversity of biotic structure without consuming as much space and therefore increasing the opportunity costs of new property development.

From the point of view of investors in the rental market, whether real estate developers or private landlords, the order of valuation highlighted according to the size of the local park can help in setting the rent but also in choosing the property in which to invest in order to derive future rental income. For the policymakers in charge of planning new park development projects or managing existing parks, these results also offer valuable insights. Firstly, park size affects individuals' preferences, with different sizes attracting varying levels of attendance and usage. Then, it would, of course, be desirable to develop large parks that offer opportunities for leisure, relaxation, and well-being on a large scale, but these results point out that in the context of limited or complex availability of lands, it can be preferable to build small ones rather than medium-sized parks. Secondly, if the priority is to improve social cohesion in a neighborhood then the development of a small park may be preferred. Finally, these results can lead public policies to reflect on the means of reducing the disadvantages of medium-sized parks which are undervalued, for example by reinforcing safety through better maintenance or night-time closure of the latter.

The results are robust to the use of other weighting methods, the Entropy balancing (see column 2 "Entropy" in Table 4) and the Optimization-based weighting (see column 3 "Optweight" in Table 4). The Entropy balancing method aims to balance weighted covariate distributions (Hainmueller, 2012; Tübbicke, 2022). This method adjusts the weights of the observations so that the distributions of observable characteristics are balanced between the groups. The Optimization-based weighting, also called "Stable Balancing Weight" aims to balance covariates directly using optimisation. With this method, weights are estimated by solving a quadratic problem with an approximate or exact balance constraint. The effectiveness of this method was demonstrated in the case of multi-level treatment by de los Angeles Resa and Zubizarreta (2020)

As there is no standard typology of park size, I also check the robustness of the results according to the thresholds of the park size categories (see Table 5) assuming that individuals generally do not know exactly how many hectares their local park is, but they do have in mind whether it is large or small. Thus, a slight modification of the thresholds should not change the average order of reference established in the main estimate. I carry out several tests to modify the thresholds for the park size categories. First, I reduce the threshold by 0.01 hectares (in column "Threshold 0.09 - 0.99") and 0.02 hectares (in column "Threshold 0.08 - 0.98"). Then, I increase the thresholds one by one by following thresholds reported in some studies in the literature. In the "threshold 0.5 - 1" column, I increase the threshold between small and medium parks from 0.1, initially chosen to 0.5. Indeed, Zhang and Han (2021) and Rosso et al. (2022) point out in a literature review on pocket parks that there is no clear definition of the size scale of a pocket park. However, the threshold of 0.5 hectares is often used in cities in Canada or by the city of Copenhagen in Denmark. Indeed, several articles based on the criteria of the city of Copenhagen state that a small park does not usually exceed 0.1 hectares but can reach a maximum of 0.5 hectares. Moreover, in the "threshold 0.1 - 2" column, I also adjust the size threshold between medium-sized and large parks by increasing the threshold from 1 hectare to 2 hectares. The 2 hectares threshold appears in the Sadeghian and Vardanyan (2015) literature review and also in the City of London's strategic plan in 2016[6]. In all cases where thresholds are modified, the significance and sign remain the same as the baseline. The amplitudes change, however, when the threshold changes are significant, as is the case in the last two columns of the table (i.e. for thresholds 0.5-1 and 0.1-2).

Table 5 Sensitivity to the rise and fall of size thresholds

	Baseline	**Threshold 0.09 - 0.99**	**Threshold 0.08 - 0.98**	**Threshold 0.5 - 1**	**Threshold 0.1 - 2**
Medium *versus* Large	-22.05***	-21.4***	-22.7***	-32.4***	-33.6***
	(1.17)	(1.17)	(1.18)	(1.14)	(1.22)
Small *versus* Large	-8.82***	-8.4***	-10.3***	-13.2***	-19.9***
	(1.17)	(1.17)	(1.18)	(1.14)	(1.22)
Small *versus* Medium	13.23***	13.0***	12.4***	19.2***	13.7***
	(1.15)	(1.15)	(1.17)	(1.13)	(1.18)
N	467,182	467,182	467,182	467,182	467,182
- *Small*	134,223	125,215	115,823	292,903	134,223
- *Medium*	214,450	222,258	231,459	55,770	260,892
- *Large*	118,509	119,709	119,900	118,509	72,067

Note: *** p < 0.01, ** p < 0.05, * p < 0.1; Robust standard errors in parentheses.

Still in this vein, in Table 6, I change the two thresholds according to the thresholds proposed in the literature or in the development plans of certain cities. In the column

[6]see page 315 in https://www.london.gov.uk/sites/default/files/the_london_plan_2016_jan_2017_fix.pdf

"Iran & Chile 0.5 -2", I follow the thresholds of 0.5 between small and medium parks and 2 hectares between medium and large parks used by Breuste and Rahimi (2015) on a study in Iran and de la Barrera et al. (2023) on a study in Chile. In the "Addison 0.4 -4" column, I follow the 0.4 and 2 hectares thresholds used by the Addison Park District, an association in charge of leisure activities in the village of Addison in the heart of the Chicago metropolitan area in the USA[7]. In the "Toronto 0.5 -3" column, I follow the 0.5 and 3 hectares thresholds used by the City of Toronto in Canada[8]. These three-size classification give results in sign and significance identical to those of the baseline.

Table 6 Sensitivity to other thresholds

	Baseline	**Iran & Chile 0.5 - 2**	**Addison 0.4 - 4**	**Toronto 0.5 - 3**	**4 categories**
Medium *versus* Large	-22.05***	-38.5***	-59.30***	-57.2***	-18.59***
	(1.17)	(1.19)	(1.23)	(1.22)	(1.32)
Small *versus* Large	-8.82***	-22.6***	-50.14***	-40.5***	-5.39***
	(1.17)	(1.19)	(1.23)	(1.21)	(1.32)
Small *versus* Medium	13.23***	16.0***	9.16***	16.7***	13.20***
	(1.15)	(1.16)	(1.17)	(1.17)	(1.30)
Small *versus* Huge					-21.82***
					(1.44)
Medium *versus* Huge					-35.02***
					(1.44)
Large *versus* Huge					-16.44***
					(1.45)
N	467,182	467,182	467,182	467,182	467,182
- *Small*	134,223	292,903	268,989	292,903	134,223
- *Medium*	214,450	102,212	150,902	117,819	214,450
- *Large*	118,509	72,067	47,291	56,460	92,101
- *Huge*					26,408

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Robust standard errors in parentheses.

Finally, in Table 6, I have also extended the typology to 4 categories instead of the initial 3 by adding the "Huge" category, which corresponds to parks of more than 10 hectares. In this classification, parks categorised as "Large" are therefore between 1 and 10 hectares in size. The initial choice of 3 categories is explained by the majority of 3-class classifications in the academic literature and in urban planning, but also by the methodology used. As the number of size categories increases, the sample size for each category becomes smaller, which can lead to difficulties in balancing covariates between classes. However, there are studies and urban planning documents that count 4 or 5 classes or even more (Breuste & Rahimi, 2015; de la Barrera et al., 2023; Hoshino & Kuriyama, 2010; Kara et al., 2011; Łaszkiewicz et al., 2022; Ummeh & Toshio, 2017). These additional categories will have an even wider catchment area, as some people refer to them as metropolitan or even regional parks. They will offer an even wider range of activities, some of them quite rare, making them even better known

[7] See https://addisonparks.org/wp-content/uploads/2017/02/5.-Classification-of-Parks.pdf

[8] See pages 57 and 58 of https://www.toronto.ca/wp-content/uploads/2017/08/9645-parks-plan-2013-17.pdf

than the large parks. In Lyon, for example, the 105-hectare Parc de la Tête d'Or host a zoo, while Parc de Parilly includes a racecourse. The 10-hectare threshold has been chosen on the basis of several studies using it (Breuste & Rahimi, 2015; de la Barrera et al., 2023; Hoshino & Kuriyama, 2010; Łaszkiewicz et al., 2022). Firstly, the order of preference remains unchanged from the baseline between the initial categories of small, medium and large park. The new category is the most highly valued, with an even higher marginal propensity to pay, explained by its greater reputation and the greater diversity of amenities on offer. The results should be taken with a little more caution than the Baseline, as the balances test indicates that 4 of the 22 covariates used exceed the 0.1 threshold (see Table 13). This explains why I favour a 3-class typology as the Baseline.

5.2 Heterogeneity analysis

Past literature on green spaces has highlighted heterogeneous preferences depending on spatial context and individual characteristics (see section 2). Building on these findings, Table 7 and Table 8 display the results of several heterogeneity analyses to evaluate differences in park size preference according to location and to the type of flat.

First, I split my sample in two according to the location of the municipality in relation to the center of the urban area (see column "CATE_11" in Table 7). More specifically, I estimate the effect of park size in municipalities in the center of the urban area on the one hand (column "CATE_11: YES") and those not in the center of the urban area on the other hand (column "CATE_11: NO"). For individuals living in municipalities in the center of the urban area, the same order of preference in park sizes as identified in the baseline remains, but the magnitude of the effect for comparisons with large parks is much stronger. Tenants in these areas pay 26€ (compared with 9€ in the baseline) more monthly rent for a large nearby park than for a small park, and 35€ (compared with 22€ in the baseline) more monthly rent for a large local park than for a medium-sized park. This sharp increase in the effect of large parks is linked to the scarcity of this type of space in these municipalities. For example, De Luca et al. (2021) note the lack of large green spaces in the dense city center of Bologna. The town centers are very densely populated and the pressure for land use is very high. As a result, the few parks that do exist in these areas are generally older (Thompson et al., 2022; Wu & Rowe, 2022; Zhang & Huang, 2020) and therefore enjoy a certain prestige, renowned in the local market (Zhang & Zhou, 2018). On the other hand, in the municipalities, which are not in the center, the order of preference is changed. Individuals prefer small parks to large and medium-sized parks. These municipalities are less dense and closer to the large green spaces of nature in the countryside. In this way, these vast green spaces will be able to act as substitutes for the large parks, since they will have very similar functions and uses, with the added bonus of potentially even more surface area and biodiversity. Therefore, tenants prefer small neighborhood parks to relax on a daily basis and socialize with their neighbours.

Second, I consider treatment heterogeneity according to the size of the apartments. I thus differentiate between dwellings of 30 m^2 and less (see column "SURFACE $\leq$ 30 m^2" in Table 7), that is to say generally one-room apartments occupied by a single person, from larger surface (see column "SURFACE > 30 m^2" in Table 7). This heterogeneity was inspired by Hoshino and Kuriyama (2010) who study the impact of parks size on the rents of one-bedroom flats. For dwellings of 30 m^2 and more, the order of preference is unchanged from the baseline, namely in descending order large, small, and then medium-sized park. In this type of housing, there are more inhabitants and therefore potentially more people likely to use the local green spaces (Hoshino & Kuriyama, 2010), but also people with different recreational activities. We can imagine that a larger surface area means more bedrooms and therefore potentially more families with children living here. Rey Gozalo et al. (2019) suggest that park users are more likely to bring their children to large parks because of the variety of leisure activities on offer. Also, having a large space at home, the tenants of these apartments certainly need their outdoor leisure spaces to be larger. Conversely, for tenants of small apartments, ie less than 30 m^2, the order of preference is reversed between large and small parks. Thus, they favor first the small ones, then the large ones and lastly the medium-sized parks. Hoshino and Kuriyama (2010) justify the lack of value placed on large parks in this type of dwelling by the fact that their occupants are less likely to use them or use them less often, so their disamenity, such as congestion and price, will counterbalance the benefits of their presence. For park user in this flat, this change of order and thus the preference for small park can be explain by the advantages of security and social interactions. Indeed, in small apartments of less than 30 m^2, mostly, there are people living alone (young, single, low income, elderly) who are more likely to seek in the park a place for interaction and socialization. Moreover, as they go there generally alone, they favor spaces where they feel safe, so with few people generally more known because living very close. Godbey and Blazey (1983), for example, show that safety and socialisation are essential criteria for the use of parks by older people who are less keen on physical activity. Moreover Palliwoda and Priess (2021) point out that the elderly are more fearful of overcrowding in parks because they are more disturbed by the behaviour of other users. The economic argument also applies here, people living alone means less income to pay the rent. It is therefore difficult to stay near large parks, which are rarer and more valued, which leads to an increase in the price of real estate.

Table 7 Heterogeneities by type of municipality and flat surface

		CATE11		**SURFACE**	
	Baseline	**YES**	**NON**	**> 30** m^2	**≤ 30** m^2
Medium *versus* Large	-22.05***	-34.82***	-10.05***	-18.14***	-1.70**
	(1.17)	(1.71)	(1.36)	(1.21)	(0.869)
Small *versus* Large	-8.82***	-26.08***	9.45***	-4.63***	6.71***
	(1.17)	(1.71)	(1.36)	(1.21)	(0.868)
Small *versus* Medium	13.23***	8.74***	19.50***	13.52***	8.42***
	(1.15)	(1.66)	(1.36)	(1.19)	(0.851)
N	467,182	252,257	214,925	398,819	68,363
- *Small*	134,223	84,647	49,576	112,029	22,194
- *Medium*	214,450	115,133	99,317	183,092	31,358
- *Large*	118,509	52,477	66,032	103,698	14,811

Note: *** p < 0.01, ** p < 0.05, * p < 0.1; Robust standard errors in parentheses.

Third, I inspect the differences in effects depending on the density of greenery within a radius of 1 km around the accommodation. While the order of preference remains unchanged for apartments whose green density is lower than the average of the total sample (see column "GREENNESS ≤ mean" in Table 8), small parks are no longer valued more highly than medium-sized parks for dwellings with a higher density of green than the average (see column "GREENNESS > mean" in Table 8). Recall that small parks allow passive recreation by observing the greenery and also more social interaction. In very green areas, green spaces such as tree-lined streets can fulfill these functions and be a substitute to small parks. Indeed, people in greener areas have access to more green spaces that can be substituted (Roberts et al., 2022). Franco and Macdonald (2018) show that greater residential tree cover can compensate for living at a greater distance from a play area but will simply be a complement to other urban parks. Substitutability or complementarity depends on the diversity of vegetation (Franco & Macdonald, 2018) and activities (Roberts et al., 2022). Small parks with less vegetation and offering fewer different elements and activities will be more easily substituted than larger parks by other green spaces. For example, observing nature on a bench in a small park can be done in a street with many trees, making the park substitutable for the street with trees, whereas jogging in a larger park is more difficult to do in a street with trees.

Table 8 Heterogeneities by green density and proximity to the nearest parks

		GREENNESS		**DISTMIN**	
	Baseline	**> mean**	**≤ mean**	**> 100m**	**≤ 100m**
Medium *versus* Large	-22.05***	-18.63***	-31.5***	-36.9***	-3.00
	(1.17)	(1.55)	(1.78)	(1.46)	(1.95)
Small *versus* Large	-8.82***	-16.10***	-11.3***	-20.4***	4.81**
	(1.17)	(1.55)	(1.78)	(1.46)	(1.95)
Small *versus* Medium	13.23***	-2.53	20.2***	16.5***	7.81***
	(1.15)	(1.54)	(1.74)	(1.43)	(1.91)
N	467,182	237,127	230,055	300,301	166,881
- *Small*	134,223	59,707	74,516	80,590	53,633
- *Medium*	214,450	103,300	111,150	140,363	74,087
- *Large*	118,509	74,120	44,389	79,348	39,161

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Robust standard errors in parentheses.

Finally, I analyse preferences according to the distance from the nearest park, or more precisely as a function of whether or not they are in the immediate vicinity of the nearest park. So I divide the sample in two, with tenants whose nearest park is in the immediate vicinity of their flat, i.e. 100 metres or less, on one side (see the column "DISTMIN <100m" in Table 8) and the rest on the other (see the column "DISTMIN >100m" in Table 8). While the order of preference is the same than that of the baseline for homes with the nearest park more than 100 meters away, it differs for the second case (homes with the nearest park 100 meters away or less). In the latter case, small parks are the most highly valued and there is no difference between medium and large parks. This effect can largely be linked to the literature quoted earlier (Anderson & West, 2006; Franco & Macdonald, 2018; Hoshino & Kuriyama, 2010; Osland et al., 2020; Wu & Rowe, 2022) which underlines the negative effect of larger parks on the prices of very close housing. They explain that this effect by the strong nuisance of noise and traffic associated with the immediate proximity of a larger park. In addition, such close proximity to larger parks generates very high rent premiums that that the majority of people are not prepared to pay on average (Chen et al., 2021; Immergluck, 2009). Furthermore, having a larger park in the immediate vicinity reduces the space available for other amenities that may be considered more important, such as shops or schools (Votsis, 2017).

These heterogeneity results also have interesting implications. They allow real estate investors to understand the valuation that may be made of the property on the size of the park according to the location of this property such as the degree of greenery or the type of property, namely its size. For decision-makers, they help to understand which sizes of parks to favor in new urban park development projects depending on the location. For example, it is not really interesting to design small parks in neighborhoods that are already very green because the greenery already strongly present can replace small parks. It also shows the problems caused by proximity to certain sizes of parks and can lead to certain proposals to limit them. For example, new parking spaces or better public transport connections can be considered to reduce the heavy congestion experienced by the immediate neighbors of large parks. Sound standards can also be established to reduce the large waves of noise emanating from these large parks.

6 Conclusion

Numerous studies in the literature for several decades have largely demonstrated the importance of proximity to nature offered by urban parks. Today, with the aging of certain urban centers, abandoned buildings and worn-out premises and growing concerns for the environment, many development projects such as the creation of shared gardens or new urban parks emerge to vegetate the cities. However, in cities where the pressure on land use is strong, the development of the smallest square meter must be carefully thought out. While some call for more small parks to ensure equal access, others recall that a large park allows for many more amenities.

This paper reveals the preferences of individuals in relation to different sizes of urban parks based on the behavior of the private rental market in 2017 and 2018 in large French urban areas. More specifically, I determine the size category of the park that maximizes the marginal willingness to pay of tenants. I use an identification strategy of estimating the causal effect by using a generalized propensity score in order to reduce confounding biases.

The results differ from the literature by highlighting a certain non-linearity in the preferences on the sizes of the parks. If, as stated in the literature, large parks are the most valued because of the diversity of amenities offered, then it is small parks that are preferred to medium-sized parks. Indeed, due to their small size and therefore lower radius of attraction, small parks offer more social interaction and a greater sense of security than medium-sized parks. However, I show that the order of preferences established varies according to the attributes of the dwelling, in particular the size of the latter, as well as its location, namely its centrality in the urban area, the degree of surrounding greenery and finally the distance to the nearest park.

These findings provide empirical evidence of heterogeneous preferences for certain sizes of parks related to the services offered and the attendance of these places. They provide important implications for the planning and management of urban parks. First of all, they shows that for the future development of urban parks, when a very large park is not possible, a small park can be better solution than a medium-sized park. For existing parks then, the study of preferences highlights the disadvantages of the size of the parks which lead to poor valuation. For example, it would be interesting to think about solutions aimed at reducing the noise and traffic nuisance suffered by the immediate neighbours of large parks. Furthermore, the closing at night of medium-sized parks could perhaps limit the feeling of insecurity it generates. Finally, it helps real estate developers and owners wishing to invest in rental purchases to understand what size of park is best valued according to the location and attributes of the property. Of course, these proposals for political implications should be treated with caution, as the analysis here is limited to the first stage of the hedonic model, given the data available. The results that emerge therefore militate in favour of more in-depth analysis in order to conduct a complete cost-benefit analysis.

Future research could also improve and strengthen the results and conclusions proposed here, in particular by including data on the characteristics of the tenants making it possible to strengthen the heterogeneous analyses of preferences or by incorporating a more qualitative dimension of the parks studied with, for example, information on the features included in each park, whether they are public or private and whether they are open or closed. Finally, it should be noted that the preferences revealed here are those of only one section of the population living in these urban areas, namely tenants. It would be interesting to reproduce this analysis with price data to also assess the behaviour of homeowners, and thus be able to offer conclusions for the whole population.

Supplementary information. This article contains supplementary material named ESM.pdf

Declarations

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Appendix A. Green detection with OpenStreetMap

OpenStreetMap (OSM) is a project founded in 2004 with the aim of creating a freely licensed map of the world. This map contains multiple geometries that represent roads, railways, rivers, forests, buildings and much more. Each geometry is assigned a nomenclature[9], called "tags", with information that describes it. These tags follow a pattern: **`key=value`**. From these nomenclatures it is possible to create custom maps containing only certain attributes. For this study, I use the OSM nomenclature to detect green spaces and more particularly parks. At first sight, the **`leisure=park`** scheme seems to be the selection to adopt. However, one of the limitations of OSM lies in its free nature. Indeed, anyone can modify the map at any time from anywhere. The nomenclature proposed by OSM is extremely broad, so it is difficult to master it well and to be perfectly harmonised. Thus, the same geometry will not be categorised in the same way by all individuals. Using only the **`leisure=park`** scheme will exclude many of the existing parks of the study area. A large amount of work is therefore carried out to identify the different schemes that could characterise the parks of the study area. Three keys is selected: **`landuse`**, **`leisure`** and **`natural`** with different values for each (see Table 9 and Table 10).

Table 9 Description of OSM Key

Key	Description
leisure	For places people go in their spare time
landuse	Mainly used for describing the primary use of areas of land.
natural	Used to describes natural physical land features, including ones that have been modified or created by humans.

Table 10 Description of OSM Value

Key	Value	Description
leisure	*garden*	Place where flowers and other plants are grown in a decorative and structured manner or for scientific purposes.
leisure	*park*	Open, green area for recreation, usually municipal.
landuse	*allotments*	A piece of land given over to local residents for growing vegetables and flowers.
landuse	*grass*	An area of mown and managed grass not otherwise covered by a more specific tag.
landuse	*recreation_ground*	An open green space for general recreation, which may include pitches, nets and so on, usually municipal but possibly also private to colleges or companies
natural	*scrub*	Uncultivated land covered with shrubs, bushes or stunted trees.

[9]Details about the OSM nomenclature : https://wiki.openstreetmap.org/wiki/Main_Page

Appendix B. Additional statistical analysis tables

Table 11: Urban areas and number of observations

Urban area	**Observation**	**Frequency**
Paris	315584	33,003767
Marseille - Aix-en-Provence	87473	9,14792419
Lyon	69233	7,24038544
Nice	66528	6,95749661
Toulouse	51324	5,36746266
Rennes	38028	3,97696731
Nantes	35357	3,69763419
Strasbourg (partie française)	34057	3,56168022
Grenoble	31552	3,29970739
Lille (partie française)	30073	3,1450336
Nancy	28310	2,9606591
Bordeaux	19829	2,07371633
Nîmes	17664	1,84730069
Toulon	13941	1,45794944
Bayonne (partie française)	13930	1,45679906
Pau	11355	1,18750562
Saint-Étienne	10584	1,10687446
Brest	10571	1,10551492
Clermont-Ferrand	8551	0,89426337
Tours	6153	0,64348059
La Rochelle	5324	0,55678379
Menton - Monaco (partie française)	5125	0,53597237
Ajaccio	4846	0,50679456
Alençon	4023	0,42072524
La Roche-sur-Yon	3971	0,41528708
Fréjus	3850	0,40263291
Vannes	3655	0,38223981
Arles	3305	0,34563682
Salon-de-Provence	3086	0,3227338
Montbéliard	2984	0,31206665
Draguignan	2469	0,25820796
Lorient	2466	0,25789422
Les Sables-d'Olonne	2329	0,24356676
La Teste-de-Buch - Arcachon	1805	0,18876686
Multipolarisé des grands pôles	1421	0,14860815
Challans	1238	0,12947001
Auray	869	0,09088
Arras	657	0,06870904
Vitré	351	0,03670757
Saint-Hilaire-de-Riez	304	0,03179231

Table 11 continued from previous page

Urban area	Observation	Frequency
Montbrison	294	0,03074651
Armentières (partie française)	291	0,03043277
Feurs	273	0,02855033
Autre multipolarisé	252	0,02635415
Communes isolées hors influence des pôles	163	0,01704654
Saint-Jean-Pied-de-Port	159	0,01662822
Sarzeau	155	0,0162099
La Guerche-de-Bretagne	98	0,01024884
Vienne	68	0,00711144
Saint-Palais	61	0,00637938
Mauléon-Licharre	60	0,0062748
Carnac	56	0,00585648
Boën	39	0,00407862
Sainte-Sigolène	20	0,0020916
Quiberon	20	0,0020916
Béthune	16	0,00167328
Beauvoir-sur-Mer	6	0,00062748

Table 12 Summary statistics and differences in characteristics between treatment groups

Variable	**Overall** N = 467,182[1]	**Large** N = 134,223[1]	**Medium** N = 214,450[1]	**Small** N = 118,509[1]
loyer	789 [80 - 9,949]	796 [80 - 9,949]	774 [80 - 9,147]	808 [84 - 9,487]
surface	54 [9 - 371]	56 [9 - 363]	54 [9 - 360]	54 [9 - 371]
collect_year	–	–	–	–
... *2017*	231,140 [49%]	58,007 [49%]	106,680 [50%]	66,453 [50%]
... *2018*	236,042 [51%]	60,502 [51%]	107,770 [50%]	67,770 [50%]
surface2	3,689 [81 - 137,641]	3,962 [81 - 131,769]	3,583 [81 - 129,600]	3,618 [81 - 137,641]
n_epco5	–	–	–	–
... *1*	140,037 [30%]	25,852 [22%]	63,280 [30%]	50,905 [38%]
... *2*	91,702 [20%]	23,492 [20%]	43,974 [21%]	24,236 [18%]
... *3*	71,045 [15%]	19,931 [17%]	31,548 [15%]	19,566 [15%]
... *4*	69,918 [15%]	18,112 [15%]	33,113 [15%]	18,693 [14%]
... *5*	94,480 [20%]	31,122 [26%]	42,535 [20%]	20,823 [16%]
nearestpark_distmin	195 [0 - 5,954]	216 [0 - 5,488]	200 [0 - 5,954]	170 [0 - 4,375]
greenness	45 [0 - 314]	54 [1 - 314]	43 [0 - 303]	39 [0 - 305]
DIST_TC	119,303 [3 - 474,259]	107,655 [6 - 471,939]	117,309 [3 - 474,259]	132,774 [4 - 473,532]
Part_av46	30 [0 - 100]	23 [0 - 99]	30 [0 - 100]	36 [0 - 100]
CATEAVV2020_11	252,257 [54%]	52,477 [44%]	115,133 [54%]	84,647 [63%]
AAV2020	–	–	–	–
... *001*	221,220 [47%]	56,975 [48%]	100,705[47%]	63,540 [47%]
... *002*	46,140 [9.9%]	8,152 [6.9%]	19,856 [9.3%]	18,132 [14%]
... *003*	39,756 [8.5%]	9,722 [8.2%]	19,320 [9.0%]	10,714 [8.0%]
... *004*	20,687 [4.4%]	4,980 [4.2%]	11,905 [5.6%]	3,802 [2.8%]
... *005*	33,247 [7.1%]	10,109 [8.5%]	16,787 [7.8%]	6,351 [4.7%]
... *006*	19,469 [4.2%]	6,015 [5.1%]	9,125 [4.3%]	4,329 [3.2%]
... *008*	22,489 [4.8%]	7,814 [6.6%]	7,613 [3.6%]	7,062 [5.3%]
... *010*	25,455 [5.4%]	4,568 [3.9%]	10,612 [4.9%]	10,275 [7.7%]
... *013*	19,404 [4.2%]	5,693 [4.8%]	8,712 [4.1%]	4,999 [3.7%]
... *014*	19,315 [4.1%]	4,481 [3.8%]	9,815 [4.6%]	5,019 [3.7%]

Table 13 Balance table after adjustment

	Max.Dif.Adj	
Variables	**Baseline**	**4 categories**
collect_year_2018	0.0017	0.0067
surface	0.0066	0.0297
n_epco5		
... *1*	0.0241	0.1008
... *2*	0.0058	0.0343
... *3*	0.0071	0.0120
... *4*	0.0036	0.0162
... *5*	0.0084	0.0390
nearestpark_min	0.0162	0.1656
green1000_withinarea	0.0485	0.3732
DIST_TC	0.0013	0.0721
Part_av46	0.0640	0.2196
CATEAAV2020_11	0.0235	0.0699
AAV2020		
... *001*	0.0100	0.0173
... *002*	0.0073	0.0507
... *003*	0.0006	0.0363
... *004*	0.0020	0.0200
... *005*	0.0034	0.0148
... *006*	0.0012	0.0158
... *008*	0.0008	0.0218
... *010*	0.0092	0.0145
... *013*	0.0017	0.0116
... *014*	0.0485	0.0010

Appendix C. Sensitivity of specification on location and centrality

The location of the flat is an important factor to consider, as it will influence both the rent paid and the presence and size of parks. A key variable in hedonic models is distance from the city centre. The closer you are to the city centre, the higher the rent, but it is also possible that local parks are smaller because of the strong competition for land use in this area. Working on urban areas, the main specification used in this study controls this dimension by a binary variable obtained for an INSEE classification of whether or not the municipality to which the dwelling belongs is considered to be at the centre of the urban area, noted *CATE2020_11*. With a binary variable, the covariate balance property is easier to verify than with a continuous variable. However, most hedonic models take distance (i.e. in the form of a continuous variable) as the centre of attention. I therefore carry out robustness tests by adding to the specification a covariate that controls for the distance to the town hall of each urban area, denoted *dist_AAV* (model 1 in Table 14). For fear of multicollinearity with the *CATE2020_11* variable, I also produce a model substituting *dist_AAV* for the *CATE2020_11* variable (see model 2 in Table 14).

Table 14 Robustness to changing specifications

	Baseline	**Model 1**	**Model 2**
Medium *versus* Large	-22.05***	-19.79***	-23.96***
	(1.17)	(1.17)	(1.18)
Small *versus* Large	-8.82***	-10.52***	-15.98***
	(1.17)	(1.17)	(1.18)
Small *versus* Medium	13.23***	9.27***	7.97***
	(1.15)	(1.14)	(1.16)
N	467,182	467,182	467,182
- *Small*	134,223	134,223	134,223
- *Medium*	214,450	214,450	214,450
- *Large*	118,509	118,509	118,509

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Robust standard errors in parentheses.

As the urban area is vast, it is possible that other centres will be important. In particular, I check the distance to the town hall of the municipality to which each dwelling belongs (see model 3 in Table 15). In model 4 of Table 15, I control for both types of centre, i.e. both by distance from the town hall of the urban area to which the dwelling belongs and by distance from the town hall of the municipality to which the dwelling belongs. Finally, the limit to taking the distance to a centre, whatever it may be, is that observations with the same distance can be matched but located on opposite sides of the centre (for example at the same distance but one to the south and the other to the north of the centre). The South/North/East/West axis can be important, as the characteristics of the neighbourhoods can be very different even if they are the same distance from the centre. I therefore check this dimension by adding the latitudes and longitudes of the dwellings to the initial specification (see model 5 of Table 15).

Table 15 Robustness to changing specifications 2

	Model 3	**Model 4**	**Model 5**
Medium *versus* Large	-21.36***	-19.18***	-20.41***
	(1.17)	(1.17)	(1.17)
Small *versus* Large	-8.64***	-10.04***	-6.04***
	(1.17)	(1.17)	(1.17)
Small *versus* Medium	12.72***	9.14***	14.37***
	(1.15)	(1.14)	(1.15)
N	467,182	467,182	467,182
- *Small*	134,223	134,223	134,223
- *Medium*	214,450	214,450	214,450
- *Large*	118,509	118,509	118,509

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Robust standard errors in parentheses.

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