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Impact of the Green Axes Initiative on Rental Prices in Barcelona: A Differences-in-Differences Analysis

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Abstract

This paper investigates the effects of the Green Axes (GA) urban redevelopment in Barcelona's Eixample district on nearby apartment rental prices. Using empirical data from a major real estate platform, the study finds significant price increases for apartments within proximity to the newly created green spaces, most significantly at the 100m buffer. The results indicate a 15.14% rise in rents for apartments within 50m of the GA, 8.45% for those within 100m, and 3.98% for those within 500m. These increases are higher than those observed in previous studies of similar urban interventions, which might be explained by Barcelona's high density and lack of green spaces. The extent of the impact is most likely found between 500m and 1000m, nonetheless, apartments being affected up to 2000m can't be overruled. The study also identifies that lower- and mid-floor apartments experienced relatively larger rent increases compared to higher-floor units. However, the paper highlights concerns related to green gentrification, potentially leading to the displacement of middle- and low-income households. These findings suggest the need for specific policies that balance the benefits of urban greening with socially responsible measures to mitigate adverse effects on rent prices.

Aknowledgements

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1 Introduction

The study of urban green spaces (UGS) has become a recurrent topic in recent years given rising concerns about climate change and citizens' general well-being. Although most studies focus on the potential health and environmental benefits derived from UGS, there is an increasing literature focusing on its impact on the housing market. Improved amenities of public spaces might inflate housing and rental prices of nearby homes, which given the current state of the housing market might lead to aggravated social inequalities. This is the case of Barcelona, a city that has seen a drastic increment in rental prices, with a 26.27% increase in the last 5 years[1], Pérez-Ruiz et al. (2024) state this to be motivated by a high demand for housing, which in turn is artificially inflated by large real estate owners, together with a lack of effective rent containment measures.

The City Council of Barcelona started in 2002, with a plan presented by the Local Urban Ecology Agency of Barcelona[2], to lead the city towards more green infrastructure. Most recently, in what is the object of study in this paper, the first phase of Green Axes Plan[3] was implemented in the Eixample, a central district of the city. The plan proposed the transformation of four major streets: Consell de Cent, Rocafort, Comte Borrell, and Girona; and an additional small section of Enric Granados, securing 5.6 km of new UGS (Ajuntament de Barcelona, 2024b), completed in the beginning of May 2023.

Green Axes (GA) are a form of green urbanization which consists of pacifying streets, i.e. closing them to traffic; improving the soil drainage of rainwater, i.e. reducing the presence of asphalt; and the creation of new green spaces, i.e. tree plantation and urban gardens. Thus, GA have been found to provide urban residents with recreational, health, and aesthetic benefits, and potentially improve their quality of life (Bockarjova et al., 2020; Mueller et al., 2021; Nieuwenhuijsen et al., 2024; Opbroek et al., 2024; Palència et al., 2021). Similar developments had already been implemented in the years 2017 and 2018 in Sant Antoni, Poblenou and Horta neighbourhoods, but none of this magnitude (Amati et al., 2024; Magrinyà et al., 2023), which led to a tense political scene with growing opposition to the GA[4] (Magrinyà et al., 2023; Marquet

[1] Using the database of the Housing Agency of Catalonia (Agència de l'Habitatge de Catalunya), which indicates a rise of 26.27% in rental prices in Barcelona between the first quarter of 2019 and the first quarter of 2024. Source:Housing Agency of Barcelona.

[2] The Local Urban Ecology Agency of Barcelona presented a plan called "Barcelona, Ciutat Mediterrània, Compacta i Complexa. Una Visió de Futur Mes Sostenible" to redefine the urban planning of the city increasing UGS and improving mobility (Rueda, 2002).

[3] Launched as part of the superblocks plan, its final implementation was developed following the international competition called New Green Axes—Barcelona Superblock held in 2020–2021 (Magrinyà et al., 2023).

[4] Due to the construction of the superblocks in Poblenou, Horta and Sant Antoni, the residents discontent due to not being involved in the process led to some discontent (Magrinyà et al., 2023).

et al., 2024). Complaints claimed a potential rise in crime due to the creation of more hidden and empty spaces and obstruction of business activity.

Most importantly, GA potentially calls for increased rental prices in the city centre due to improved green amenities in the reformed streets. Anguelovski et al. (2018), Cui et al. (2018), Noh (2019) and Piaggio (2021) found this to be the case when looking into different types of green areas. As a result, property owners capitalize on green locational attributes, increasing their wealth. Conversely, tenants suffer an increase in their monthly rent, thus existing low and middle-income residents are in danger of being displaced by higher-income citizens, giving way to the concept of *green gentrification* (Anguelovski et al., 2023; López-Gay et al., 2020).

There is currently no literature on how the GA affected the rental market in Barcelona, nor the sales market for that matter. Hence, this paper addresses this gap by looking into the effect of the newly built GA in the Eixample district on the rent prices of nearby apartments. This study presents key evidence on relevant indicators for green gentrification, suggesting, on the same line as Anguelevski et al. (2018), the importance of implementing ecologically and social policies simultaneously, thus being useful for present and future urban planning.

This study employs a Differences-in-Differences (DiD) method, as the main analysis, to estimate the price effect on rentals. As a first approach, the Hedonic Pricing (HP) principle is applied to establish the area of influence of the GA on prices. Cross-sectional data between Jaunary 2018 and May 2024 from Idealista, a major housing platform in Spain[5], is used. For the main DiD analysis observations within 50m, 100m, and 500m of the GA are defined as the treatment group and those between 2000m and 6000m away from the GA as controls. 30th of April of 2023, which is the date at which the construction work was finalized, is the cutoff date for the definition of pre- and post-policy.

The results show an increase of 15.14% in monthly rent prices for homes that have direct access to the GA (within 50m), an 8.45% increase for homes adjacent to the GA (within 100m), and a 3.98% for homes within walking distance (500m) of the GA. Moreover, the HP model suggests the extent of the impact up to 2400m around the GA, however the effect is small after the 500m buffer. Further sensitivity tests present more steep results suggesting those to be interpreted as the lower bound.

The work is structured as follows: Section 2 presents an exhaustive literature review on UGS

[5] Idealista was founded in 2000 and is regarded as one of the biggest housing platforms in Spain, listed as number 1 in multiple sites, which has between 10,000 and 20,000 rental listings per month.

effect on both housing and rental prices; Section 3 provides context on Barcelona and the GA implementation; Section 4 describes the DiD model used and the descriptive statistics; Section 5 presents the parallel trends formal test; Section 6 explains the results; Section 7 contains the heterogeneity analysis at different floor levels; Section 8 provides the sensitivity analysis with multiple robustness checks; Section 9 goes over the limitations of the paper. Finally, Section 10 concludes.

2 Literature review

Investigating how locational attributes affect property prices is an important topic of research since it has economic and social value. Moreover, it can inform about unforeseen adverse effects of policies. On those lines, numerous scholars have focused on capturing the effect of green amenities on residential prices (Bockarjova et al., 2020; Cui et al., 2018; Donovan and Butry, 2011; Jo Black and Richards, 2020; Levere, 2014; Piaggio, 2021), given that UGS are usually understood as an improvement to the community. The current studies focus mostly on the effect on sale prices (Bockarjova et al., 2020; Jo Black and Richards, 2020; Kang and Cervero, 2009; Levere, 2014; Liebelt et al., 2018a; Noh, 2019), generally finding an increase in property value if the UGS is properly maintained, sufficiently lighted, and perceived as safe (Liebelt et al., 2018a; Lo and Jim, 2012; Piaggio, 2021). Most interestingly, multiple studies have been conducted using data on rental prices (Cui et al., 2018; Donovan and Butry, 2011; Jun and Kim, 2017; Liebelt et al., 2018a,b; Piaggio, 2021; Yu et al., 2020; Zambrano-Monserrate et al., 2021), which bear additional information given the different natures of homeowners and tenants. Overall, research informs about the risk of population replacement, given that low- and middle-income earners value green amenities less than high-income earners (Cui et al., 2018; Donovan and Butry, 2011)

Nevertheless, literature on Barcelona is scarce and null in the case of GA. Interestingly, there is a wide range of literature looking into environmental and health improvements, such as pollution levels (Palència et al., 2021), surface temperature (Kim et al., 2024; Mueller et al., 2021), and general well-being (Opbroek et al., 2024; Vidal Yañez et al., 2023), but there are currently no studies on how the Superblocks or the recently implemented GA affected property values.

The rental market in Barcelona seems to be sensitive to public policies. In close relation to the topic of this paper, Anguelovski et al. (2018) conducted a study on the effect of UGS on sale prices in historically low-income neighbourhoods[6] and concluded that there was an increase between 12% and 31%, within a 100m buffer. A recent study by García et al. (2010) has estimated an effect of local public investment on sale prices of 0.10% per every 1000€ of public spending. Additionally, Garcia-López et al. (2020) looked at how long-term rentals are affected by short-term ones, finding a 7% increase in areas with high Airbnb activity.

From a more global perspective, research on housing transactions is more consistent than the one on rental prices, finding price increases around 20% (Bockarjova et al., 2020; Chen and Jim, 2022), with an upper and lower limit of 35.3% and 10.85% as established by Jo Black and Richards (2020) and Noh (2019) respectively, depending on the area and approach used. Conversely, the effect on rental prices is less pronounced but still bears significant increases up to 8.2% (Piaggio, 2021). In both cases, results are not always positive, UGS are sensitive to safety concerns or proximity to other locational amenities, i.e. the city centre. In those cases, UGS can become disamenities. Additionally, the effect differs depending on income level and floor level, with high-income households being more prone to having access to green spaces (Cui et al., 2018), and apartments in the same level as the green area responding more strongly to green amenities (Jo Black and Richards, 2020).

<u>Transaction prices</u>

In the literature the definition of green spaces is diverse, it can refer to parks, greenlines, greenways, greenbelts, green infrastructure, or tree plantations. No similar implementations to the GA have been examined to my knowledge, arguably the most similar policies are small parks or greenway construction in central areas of a city. When looking into small parks or gardens on sale prices the effect is more contained compared to the others. Following a meta-analysis implemented in Utrecht, using 37 studies, Bockarjova et al. (2020) establish that the effect of a green neighbourhood square reaches a maximum cumulative effect of 4.11% within 100m. Similarly, in the case of residential gardens, which are of a smaller size and more dispersed throughout the city, Chen and Jim (2022) find a more pronounced accumulated effect of 17.2%. Conversely, looking into large-scale UGS, Bockarjova et al. (2020) suggest an increase between 1.82% and 2.06% in house price as a consequence of moving 100m closer to an urban forest or park, reaching a maximum cumulative effect of 20% for properties found directly fronting the park compared to those found at 2900m.

On the same line, greenways are large linear transformations of public spaces, generally railways or freeways, and seem to substantially affect prices, most likely due to higher marginal

[6] It refers to Horta-Ginardó, Sant Andreu and Nou Barris.

benefits of large UGS in central areas of the city. Noh (2019), by conducting an Adjusted Interrupted Time Series DiD, studies the effect of a railway transformed into a greenway in Whittier, California, and estimates a 10.85% premium in the sales price of the properties located within 400m after the conversion. Seemingly, Jo Black and Richards (2020), using DiD, measure the effect of the New York High Line transformation, a green way of similar characteristics to the one in Whittier, California, and find a much steeper effect, with homes adjacent to the greenway (within 80 m of the High Line) experiencing a 35.3% higher sale prices compared to those between 80 and 800 m. Levere (2014), also studying the New York High Line, finds a premium of 10%, but in his case, a 533m treatment group is used which might explain the attenuation of the effect. Finally, Kang and Cervero (2009) conducted a study in Seoul, where a freeway was replaced by an urban stream and a linear park, commercial parcels (non-residential) within 100 metres of the greenway raised in value about 13.27% more per square metre than otherwise-comparable parcels lying more than 500 metres away after the intervention.

Rental prices

The demand in the rental market seems to be more elastic than that of the sale market. Although the literature on rental prices is concentrated on larger UGS like green belts, prices strangely go over a 10% increase. Piaggio (2021) uses San José survey-based data on rental prices to estimate how proximity to non-developed natural areas, metropolitan parks, and neighbourhood parks affects them. He estimates an elasticity of 0.082[7] for an average household 400m away from a park, which is equal to a 2.05% increase in monthly rent if the distance is reduced by 100m[8], or 8.2% higher rental prices for those households directly facing the urban green areas[9]. Similarly, increasing the tree population is one of the main assets of the GA, hence, by also studying rental prices, Donovan and Butry (2011), focus on the effect of trees using data from Portland, Oregon. They found that one more tree in the street fronting the apartment can lead to a 1.67% increase in the rental price. Further literature supports the premise that renters behave differently to homeowners, the former being less prone to proximity to green spaces, prioritizing other factors such as proximity to the city centre, which might be explained by average lower income levels compared to owners (Zambrano-Monserrate et al., 2021). Cui et al. (2018) add that owners tend to be more responsive to locational features that enhance the quality of life, such as a good environment. Conversely, tenants are usually relatively younger and prioritize living closer to bus stops and public transport convenience (Cui et al., 2018)

[7] Elasticity can be interpreted as the % increase in the outcome variable of a 1% increase in the independent variable.

[8] 100m meters are a 25% of 400m, thus a $25 \times 0.082 = 2.05$.

[9] $100 \times 0.082 = 8.02$.

Heterogeneity of estimates

New UGS do not always increase property value. For example, Liebelt et al. (2018a,b), using the HP method, study the case of Leipzig and find a negative impact of parks on sold flat prices, estimating a decrease of 14€$/m^2$ if the flat is 100m closer to the park. This behaviour is also observed for tenants, depending on the context, proximity to the parks might prompt a drop between 0.45% and 3.95% compared to those 1000m away, as suggested by Donovan and Butry (2011) and Jun and Kim (2017) respectively. This could be explained through undesired effects such as criminal activity and feeling unsafe around the green area (Donovan and Butry 2011; Liebelt et al., 2018a,b), or due to other locational disamenities such as loud night noises or bad odours (Liebelt et al., 2018a,b; Lo and Jim, 2012; Piaggio, 2021).

Moreover, not all renters have the same preferences. As already suggested with the difference in incomes of tenants and owners, income also drives differences between renters. High-income households show higher preferences for environmental amenities (Zambrano-Monserrate et al., 2021). Along those lines, Cui et al. (2018), use 2016 rent data from Beijing and observe that low-priced renters are reluctant to live near green spaces, whereas high-income earners have a preference for it. They do so by breaking the sample into ten quantiles and show that lower-priced renters (those in the first quantile) see a decrease in the monthly rent of 0.19% if the distance is reduced by 100m which is equivalent to paying 2.02% [10] less for living directly next to the park compared to those living 1086m away (mean distance of the sample). Whereas the higher-priced renters (those in the top percentile) show a positive elasticity, attributing 0.23% higher value for houses found 100m closer to the park and 2.55% more if compared to those living 1086m away[11]. Although Cui et al. (2018) do not control for crime activity, thus there is the risk of omitted variable bias (OVB) with lower-priced apartments likely being found in less safe areas, it helps illustrate the inequality concerns that may arise from new UGS, namely green gentrification, as suggested by Anguelovski et al. (2023, Kotsila et al. (2021), López-Gay et al. (2020), or Wolch et al. (2014).

Finally, on an interesting note, the effect of green infrastructure decreases as distance from the green space is gained. Nonetheless, this also holds true for vertical proximity, since depending on the floor level at which the apartment is found, it might benefit more or less from the policy implementation. On those lines, Jo Black and Richards (2020), find that those apartments found

[10] The mean distance is 1086.46m, hence a 100m decrease supposes a 9.2% decrease. Then 9.2x0.0202 = 0.1858, approximately 0.19%; and 100x0.0202 = 2.02%, since 1086 represents 100%.

[11] Following the same logic, with the price increasing by 0.0255% if the distance to the park is reduced by 1% and the mean distance is 1086.46, a 100m decrease equals a 9.2% decrease which is 9.2x0.0255 = 0.2346, approximately 0.23%. A 1086m decrease is a 100% decrease, implying a 2.55%.

at the same height as the New York High Line, respond more strongly, with an increase around 76%, doubling estimates found at other floor levels.

3 Historical context and Green Axes implementation

On the 15th of August of 2022, the construction work began for the implementation of the first GA in the Eixample district of Barcelona, in the streets of Consell de Cent, Rocafort, Comte Borrell, and Girona, in addition to a small section of Enric Granados street (Ajuntament de Barcelona, 2024b). Although originally part of the superblock plan, policymakers opted for a paced implementation, leading to the Green Axes Plan starting with the implementation of GA in the neighbourhoods of Sant Antoni, Poblenou and Horta, between the years 2017 and 2018.

3.1 Barcelona's urban challenges and housing crisis

Context of Barcelona

Barcelona is a high-density city. Its metropolitan area contains two of the top three most densely populated square miles in Europe[12]. The district of l'Eixample is a central district which spans across 7.46 km^2 and is the most populated in the city, with 268,824 inhabitants as of 2023. It also is the most densely populated in the city of Barcelona, with 36,035 hab/km^2 (Magrinyà et al., 2023). Barcelona suffers some of the highest air pollution levels due to its excessive motorized traffic (Nieuwenhuijsen et al., 2024). The car occupies 60% of the road space and it only represents 1 of every 4 trips made (Ajuntament de Barcelona, 2024b). At the start of the millennium, the density of cars in Barcelona was 6000 per km^2, compared to 3000 per km^2 in Madrid and 1200 per km^2 in London (Magrinyà et al., 2023). A factor that contributes to the high density and pollution is the lack of green spaces that are unevenly distributed across the city. Only 10% of the city area is assigned as green space, corresponding to $7m^2/hab$ (Pàmies, 2023). And if we look at the percentage of the population with access to green spaces[13], the Eixample (60.6%) shows the lowest levels after Gràcia and Ciutat Vella with 37.8% and 40.7% respectively (Magrinyà et al.,2023).

Barcelona's housing crisis

Moreover, the rental market is currently undergoing a crisis worldwide, with big cities reaching record prices. Barcelona has been severely impacted by this crisis, being one of the cities with

[12] Archeive Urban Europe. Source: Archeive Urban Europe.

[13] Here the 15min standard is used, thus using population within 500m of a UGS.

the lowest available housing stock in Europe. Owners under 35 years of age went from 70% in 2011 to 32% in 2022 (Pérez-Ruiz et al., 2024), additionally, there has been an increase of 26.27% in rental prices in the last 5 years[14], which translated into four of every ten residents spending up to 40% of their salary on accommodation[15]. Paradoxically, the renting population in the city has been rising, going from 38.2% to 44.8% between 2017 and 2024, even up to 56.6% for citizens under 30 years of age (Pérez-Ruiz et al., 2024).

On those lines, multiple policies have been implemented to ease the high market pressures, such as legislation to regulate long-term and short-term rental prices, with the *Catalan Rent Contention Law*[16] (*Llei de Contenció dels Lloguers*), active between September 2020 and March 2022; the *Law on the Right to Property*[17] (Llei del Dret a la Propietat), implemented in May 2024; the recent City Council initiative to eliminate all permits for touristic apartments in the city by 2028[18] (Ajuntament de Barcelona, 2024a), which would increase the supply of long-term rentals by 10,101 new apartments; or, lastly, the increase of social housing provision up to 30% (Ajuntament de Barcelona, 2024a), a substantial increase compared to the 2% available in 2018[19].

3.2 Superblock Plan

Under this scenario, following the initial urbanisation plan of l'Eixample, developed by Ildefons Cerdà in 1855[20], a number of ideas emerged to reform the district of l'Eixample to promote air-flowing and a healthier environment. In 1970 urban interventions started encouraging traffic

[14]Using the database of the Housing Agency of Catalonia (Agència de l'Habitatge de Catalunya), which indicates an increase of 26.27% in rental prices in Barcelona between the first quarter of 2019 and the first quarter of 2024. Source:Housing Agency of Barcelona.

[15]Ministerio de Fomento. Observatorio de Vivienda y Suelo. Boletín Especial Alquiler Residencial. Dirección General de Arquitectura, Vivienda y Suelo. 2017. Available online: Ministerio de Fomento, also cited in Blanco-Romero et al., 2018.

[16]The Catalan Rent Contention Law (Llei de Contenció dels Lloguers, Llei 11/2020), introduced the rental price index, a government-established tool designed by the Housing Agency in Catalonia to provide a benchmark for rental prices based on factors such as location, property size, and amenities. Source: Portal Jurídic Gencat.

[17]The Llei del Dret a la Propietat (Law on the Right to Property) in Catalonia, formally known as the Law 5/2006, was enacted to regulate the protection of property rights and ownership in the region. It addresses the rights and obligations of property owners and tenants, focusing on housing accessibility, social protection, and legal safeguards. Established in 2006, the law aims to balance individual property rights with the broader social interest in housing stability and affordability. This May of 2024, a law at the Spanish level was approved (Llei del dret a l'habitatge, Gencat).

[18]The City Council of Barcelona approved on the 21st of June, will not give more licences for touristic apartments, once the active ones now have expired they won't be renewed, following a law approved by the Catalan Government, the 7th of November 2023, which required more strict regulation on touristic apartments. Source: Gencat.

[19]Barcelona Metropolitan Housing Observatory.

[20]The Pla Cerdà, designed by Ildefons Cerdà in 1859, was an urban development plan for the expansion of Barcelona, known as the Eixample. It introduced a grid-based layout with wide streets, chamfered corners, and public spaces, aiming to improve sanitation, sunlight, and mobility, reflecting Cerdà's innovative vision of modern urban planning. Source: Pla Cerdà.

pacification (e.g., traffic was closed in the Ciutat Vella district between 1973 and 1991[21]). It was not until the year 2004 that the concept of superblock (*superilla*in Catalan) emerged at the Urban Ecology Agency of Barcelona (BCNEcologia). A superblock consists of closing four road junctions in a grid of nine apartment blocs, the interior being pedestrian-only. The original plan was to create 503 superblocks covering the entire city (Nieuwenhuijsen et al., 2024). The superblocks propose a new road hierarchy that establishes a network of basic roads, where vehicles will circulate mainly (30 km/h) and a network of local roads with priority for people and cyclists (10 km/h). Under this scenario, 2 out of every 3 streets are pacified, i.e. allowing mainly only active transport and the incorporation of green space (Nieuwenhuijsen et al., 2024). The first three superblocks were implemented between 2016 and 2018 in Poblenou, Sant Antoni, and Horta, which consisted of small interventions affecting only a few streets (Ajuntament de Barcelona, 2024b).

3.3 Green Axes

Between 2019 and 2022, after the implementation in the first three regions, the city strategy changed from being superblock-centered to prioritizing the construction of the GA in the Eixample district, which supposed a reduction in the number of streets being pacified to 1 out of every 3 streets instead of 2 out of 3 streets (Magrinyà et al., 2023; Nieuwenhuijsen, 2024). Originally 21 connected GA were envisaged in the Eixample, with a total of 33 km of street and 21 new squares, which would provide an additional 3.9 ha of new public spaces. In total, the Eixample neighbourhood would gain 33.4 ha of new pedestrian areas and 6.6 ha of urban green areas (Ajuntament de Barcelona, 2024b), represented in Figure 1, with green dotted lines. Notably, the streets marked in dark green refer to the structural and tactical urbanisation reforms in the Sant Antoni neighbourhood done between 2017 and 2018 (Ajuntament de Barcelona, 2024b).

Nonetheless, in 2020–2021, the plan of action only considered four major street sections and an additional minor one, amounting to 5.6 km of green street, which are the ones being analysed in this paper, represented in Figure 1 with solid light green. The four red dots represent the $2000m^2$ squares in each intersection. The construction work started on the 15th of August 2022 and ended on the 30th of April 2023 [22] (Ajuntament de Barcelona, 2024b). On a more detailed note, the streets that have been transformed are 2.8km of Consell de Cent, a major longitudinal

[21] Source: Betevé.

[22] Due to a change of governance the construction work was delayed until the beginning of July 2023, although most of the work was already finished by May. Throughout the analysis only the end date of May is used, nonetheless, a robustness test is conducted in Section 8 to ensure it doesn't lead to any bias (Ajuntament de Barcelona, 2024b).

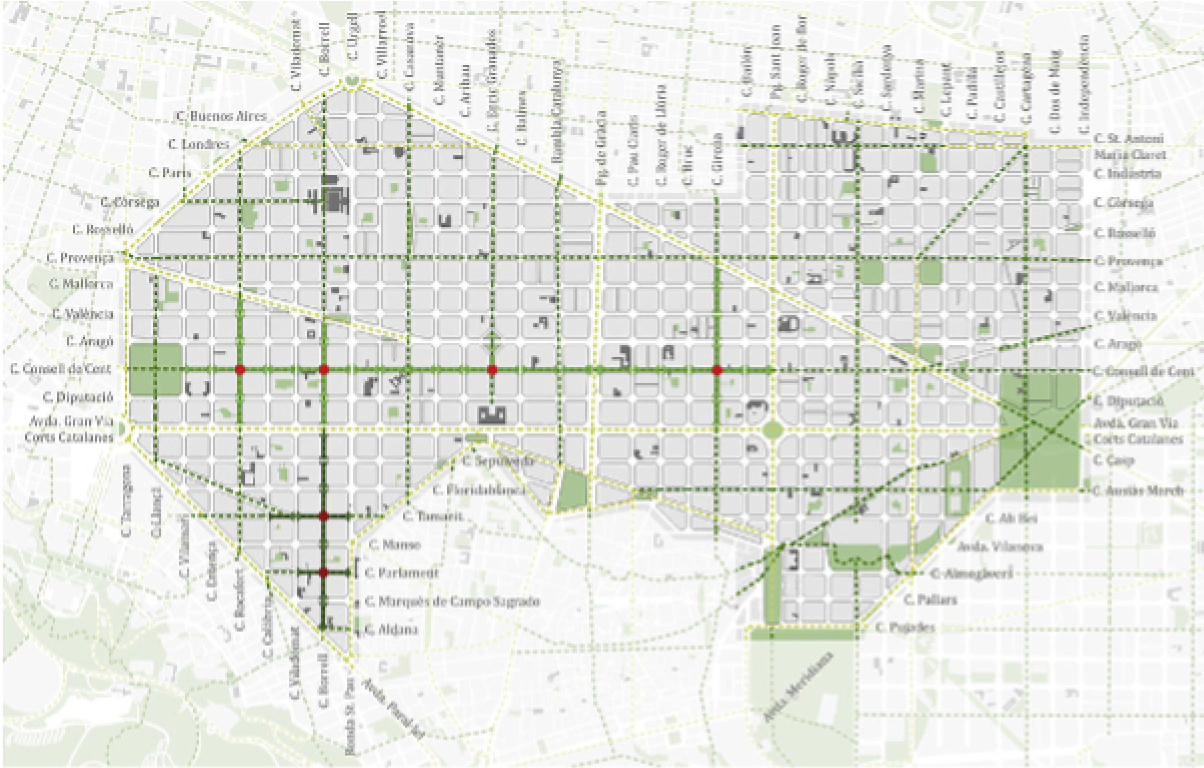

Figure 1: Eixample's Green Axes. Dark green: Sant Antoni implemented in 2019; light green: Eixample GA studied in this paper; and dotted green lines: initially planned 21 GA, not yet implemented. Source: (Ajuntament de Barcelona)

artery, between Carrer Vilamarí and Passeig de Sant Joan, and four street sections perpendicular to it. The first two Rocafort and Comte Borrell, both transformed between Gran Via de les Corts Catalanes and Avinguda Roma. The third one is Girona, transformed between Gran Via de les Corts Catalanes and Avinguda Diagonal. Finally, a small section of Enric Granados Street enables the creation of a fourth square at its intersection with Consell de Cent.

These GA introduced kerbless "panot" paving, substituting asphalt and the different levels between road surfaces, with increased green areas, moving from the standard 1% green area on the streets to an average of 14%, with 438 new trees planted, allowing for better drainage of rainwater and soil quality. Cars have been limited to 10 km/h speed, giving priority to pedestrians, and 1000 items of furniture, such as benches and children's games, have been placed all around the area, fostering social use of these streets (Ajuntament de Barcelona, 2024b).

Figure 2 and 3 illustrate the change in the intersection between Enric Granados and Consell de Cent, presenting a before and after comparison.

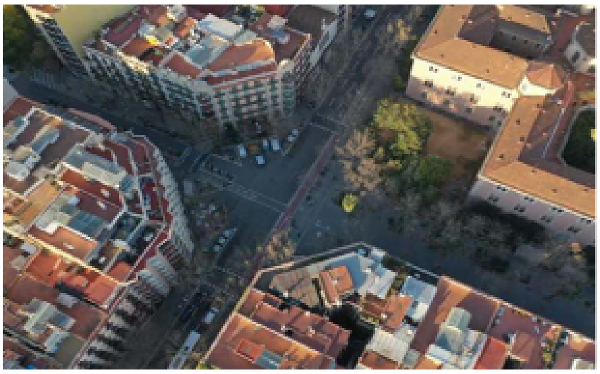

Figure 2: Plaça Enric Garanados - Consell de Cent (2024). Source: Ajuntament de Barcelona

Figure 3: Plaça Enric Garanados - Consell de Cent (2024). Source: Ajuntament de Barcelona

4 Data description and methodology

The main analysis conducted in this paper consists of a Differences-in-Differences (DiD) approach. All GA are treated as a single unit, hence when using different proximity buffers around the GA to assign treatment (within 50m, 100m, and 500m) and control groups (between 2000m to 6000m), the distance of each observation is measured as the distance to the closest GA. The dates of start (15th of August of 2022) and end (30th of April of 2023) of construction are used to define the $pre-$ and $post-$policy periods, disregarding the observations in between to ensure the totality of effect is captured. The equation below represents the main regression of the analysis.

$$ln(Price_i) = \alpha + \beta_1 Treatment_i + \beta_2 Post_i + \beta_3 (Treatment_i \times Post_i) + \phi_t + \phi_l + \gamma X_i + \mu_i \quad (1)$$

Equation (1) follows the standard DiD regression, which is used throughout the analysis. The dependent variable is the natural logarithm of the monthly rent price, $ln(Price)$. α represents the constant term; β_1 captures the effect of the dummy variable $Post_i$, which is equal to 1 if the observation i was after the construction of the GA was finished; β_2 captures the effect of the variable $Treatment_i$, which is equal to 1 if observation i is found within a 50m, 100m, or 500m of the GA, and 0 otherwise; β_3 is the estimate of interest, and captures the effect of the interaction term between $Post_i$ and $Treatment_i$ ($Treatment_i \times Post_i$). Time-fixed effects at the yearly level (ϕ_t) and location-fixed effects at the Statistical Basic Area level[23] (Àrea Estadística

[23] Àrea Estadística Bàsica, which is a territorial level between the neighbourhoods and the census sections. In the preparation the guideline of the entire territorial system was followed: each territorial level must be contained in the immediately superior. They would have to be in total between 200 and 250 zones: 1. Purely statistical purpose. They do not correspond to neighbourhoods. Very useful for studies, with the same function as the previous zoning of 248 ZRP. 2. Do not break blocks of houses. 3. A minimum of 500 voters, also following the Electoral Law. 4. Uniform areas within the districts (population, urban and sociological). The denomination is

Bàsica) (ϕ_l) are included, which controls for unobserved covariates. Additionally, to improve the robustness of the model I included observable descriptive characteristics as control variables, which are represented by X_i and captured by γ. Section 4.2 below explains the strategy in more detail.

4.1 Data description and statistics

For the empirical analysis, a database containing 599,384 observations on rental prices in Barcelona from January 2018 to May 2024 was provided by a major real state platform, Idealista [24]. With around 100% of rental postings in Barcelona and 17 million weekly views, Idealista is the major real estate portal in Spain. To my knowledge, even though previous versions of this data have been used in other studies, i.e. Garcia-López et al. (2020), this updated data hasn't yet. The data is cross-sectional, and each ID (reference number for a specific apartment) is only observed once in the data, nonetheless, the possibility of apartments appearing repeatedly at different points in time under a different ID can't be overruled, but for the analysis conducted this is not an cause of concern. Also, duplicates have been checked for.

The dataset contains information on two outcome variables: rental price ($Price$) and rental price per square metre ($UnitPrice$). Additionally, the respective natural logarithms have been generated: $ln(Price)$ and $ln(UnitPrice)$. Using postings isn't an unusual practice in related literature, as done by Donovan and Butry (2011), Garcia-López et al. (2020), Liebelt et al.(2018a,b), and Zambrano-Monserrate (2021), and although posted prices might slightly deviate from the real final price, Chapelle and Eymeoud (2022) find the difference between the two to be less pronounced in the case of online rent postings compared to housing sale postings.

Most importantly, the data contains the exact location of the rentals, which allowed to establish treatment and control groups in a precise manner by using a Geographic Information System (GIS), a common practice when working with spatial data, implemented by Jo Black and Richards (2020), Levere (2014), Liu et al., (2024a), and Noh, (2019). Using Open Street Map[25] with QGIS[26] allowed me to create the treatment and control groups depending on the proximity

numerical, followed by 1 to 233. Source: Territori Ajuntament de Barcelona.

[24] Idealista is one of the largest online real estate platforms in Spain, offering a marketplace for buying, selling, and renting properties. Founded in 2000, Idealista allows users to search for homes, apartments, and commercial spaces across Spain, as well as in Portugal and Italy. Source: Idealista.

[25] OpenStreetMap (OSM) is a collaborative project that creates and provides free geographic data and mapping to the public, allowing users to view, edit, and use detailed maps of the world, with applications ranging from navigation to urban planning. Source: Open Street Map.

[26] QGIS (Quantum Geographic Information System) is a free and open-source geographic information system that enables users to create, visualize, analyze, and publish geospatial data. Source: QGIS.

of each observation to the GA. The buffer zones around the GA have been established at 50m, 100m, and 500m for the treatment group, and between 500m to 6000m, 1000m to 6000m, and 2000m to 6000m for the control groups, to ensure reliable results. In Section 4.2 a detailed explanation of the treatment and control groups will take place. Furthermore, I assigned each observation to a Statistical Basic Area, allowing the use of location fixed effects on a smaller level than the neighbourhood or district.

The data presents a wide range of apartment descriptive variables. The ones included in the main regression are the area of the apartment (m^2); a dummy variable for lift ($lift$); a dummy variable for flat location ($flatlocation$), indicating whether the apartment faces the interior or the exterior of the block[27]; floor level of the apartment ($floornumber$); condition of the apartment ($condition$), whether it is a new building, reformed or second-hand; two dummy variables for temporary ($temporaryrental$) and vacation rental ($vacationrental$); number of rooms ($roomnumber$); and bathroom number ($bathnumber$). The variables have been chosen depending on availability and relevance, following García et al. (2010) and Liebelt et al. (2018a,b) procedure. All included controls bear significant coefficients, see Appendix Table 11.1.

Although the data set contains other variables such as the age of the apartment, or dummy variables for the terrace, swimming pool, garden, and top floor, due to a substantial number of missing values, they were excluded from the analysis.

Moreover, the data presented large outliers, partly attributed to errors. I conducted a data cleaning process to get rid of outliers, deleting observations with rental prices outside the 99% interval, and did the same for the m^2 and $UnitPrice$ (29,824 observations deleted) to ensure a more reliable study avoiding outliers to drive results, following the practice of Jo Black and Richards (2020) and Liebelt et al., (2018a,b). Additionally, I deleted floor levels under 0 and set an upper limit at the 11th floor (32,777 observations deleted) since buildings of the Eixample district contain no more than 11 storeys, enhancing comparability. The same was done by limiting to 6 the number of rooms (only 471 additional observations deleted), and the number of bathrooms to 4 (0 additional observations deleted), following Yu et al. (2020). The number of observations dropped is negligible and prevents biases caused by outliers.

[27] All apartments in the sample are expected to have windows, although there is not a variable for it, nonetheless whether the apartment faces the interior or the exterior of the block gives information on access to natural light and street noise pollution. Note that only 7% of apartments face the interior.

Table 1: Descriptive Statistics by Treatment Group

	OUTLIERS			CLEAN		
	Treat100m	Control	T-test	Treat100m	Control	T-test
Price	1587.71	1357.63	-230.08***	1454.94	1258.33	-196.61***
	(4391.53)	(3889.23)	(30.45)	(536.03)	(546.68)	(4.32)
UnitPrice	18.74	16.53	-2.21***	17.54	15.96	-1.58***
	(52.82)	(46.85)	(.367)	(5.38)	(4.63)	(.037)
ln(Price)	7.25	7.08	-.170***	7.22	7.06	-.162***
	(.397)	(.436)	(.003)	(.335)	(.374)	(.003)
ln(UnitPrice)	2.84	2.74	-.103***	2.82	2.73	-.089***
	(.348)	(.306)	(.002)	(.289)	(.267)	(.002)
Area(m2)	92.73	85.50	-7.23***	86.39	81.69	-4.70***
	(184.51)	(52.75)	(.617)	(30.449	(33.33)	(.261)
Distance to GA	43.08	2891.74	2848.668***	43.05	2882.38	2839.33***
	(31.18)	(777.63)	(5.64)	(31.16)	(772.48)	(5.74)
Lift	.917	.772	-.145***	.918	.774	-.144***
	(.276)	(.419)	(.003)	(.274)	(.418)	(.003)
Room number	2.47	2.47	-.004	2.47	2.45	-.019**
	(1.04)	(1.11)	(.008)	(1.00)	(1.05)	(.008)
Bath number	1.49	1.44	-.052***	1.47	1.40	-.072***
	(.594)	(.661)	(.005)	(.558)	(.588)	(.005)
Floor number	30.24	29.95	-.284*	30.15	29.73	-.421**
	(20.24)	(.169)	(22.10)	(20.15)	(22.01)	(.172)
Condition	3.00	2.99	-.001**	3.00	2.99	-.002***
	(.067)	(.085)	(.001)	(.062)	(.084)	(.001)
Flat location	1.09	1.06	-.029***	1.08	1.06	-.029***
	(.280)	(.230)	(.002)	(.277)	(.228)	(.002)
Temporary rental	.093	.055	-.037***	.084	.054	-.030***
	(.290)	(.229)	(.002)	(.278)	(.227)	(.002)
Vacation rental	.024	.018	-.006***	.023	.018	-.005***
	(.153)	(.132)	(.001)	(.148)	(.132)	(.001)
Outliers	YES	YES	YES	NO	NO	NO
Treatment group	YES	NO	-	YES	NO	-
Observations	19045	144981	-	18094	136413	-

Standard deviation in parentheses for Treat100 and Control
Standard error in parentheses for T-test
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The treatment and control groups present significant differences in the outcome and control variables, however, this is not problematic since the DiD does not require them to be equal. Table 1 presents the descriptive statistics independently for treatment at 100m and the control, between 2000m and 6000m, describing the mean and standard deviation of each variable included in the main analysis, before and after the cleaning process. Furthermore, a t-test has been provided informing about differences between groups. Notice that, for the four outcome variables presented, $Price$, $UnitPrice$, $ln(Price)$, and $ln(UnitPrice)$, the exclusion of outliers decreased the mean prices relatively more for the treatment group, bringing them closer to the control group. The rest of the covariates indicate inherent differences between the two groups which justifies their inclusion as controls in the analysis. Finally, the contrast in the number of observations in each group, although it is sizable, is not a problem since the treatment group still presents a considerable amount of observations (18,094). That is because the treatment group is only formed by observations within 100m.

4.2 Main empirical strategy

When measuring the attributed value of locational features to property prices, a common empirical method is to use HP[28], which allows to estimate the value of non-tradable features that add to the selling or rental price of a home. Nonetheless, this method is usually applied using OLS and relies on strong assumptions. An improvement to this methodology is the DiD method, which is a widely used methodology by academics in this field, namely, Jo Black and Richards (2020), Liu et al. (2024a), Noh (2019) and a working paper by Yu et al. (2024) use it, since it secures more reliable estimates, given that the required assumptions are more attainable. To estimate the causal effect the parallel trends assumption needs to be fulfilled, that is both groups follow statistically the same trends before the policy is implemented, allowing to overcome the causal inference problem, meaning the trend followed by the counterfactual before and after the GA are constructed is equal to the tend the treated group would have followed in the absence of treatment. So, the DiD relaxes the strict OLS assumptions by controlling for time-invariant factors, reducing the likelihood of omitted variable bias, and allowing for inherent differences between the groups as long as common trends are followed. The test for parallel trends is presented in Section 5.

So, getting into the specifics of the empirical strategy of the paper, here I describe the reasons for the chosen post-policy dates, and why 50m, 100m, and 500m have been chosen as the distances of interest.

Definition of the *pre* and *post* policy period

In the first place, the policy was not implemented *de facto*, construction work lasted approximately 8 months, between the 15th of August of 2022 and the 30th of April of 2023, although some sources suggest the construction work was finalized by July 2023, for the main approach it is disregarded, however, a sensitivity test is conducted in Section 8. Throughout the analysis,

[28]The Hedonic Pricing Method is an economic model used to estimate the value of non-market goods, such as environmental benefits, by analyzing the impact of those goods on market prices (e.g., property prices). It isolates the contribution of factors like proximity to urban green spaces by observing how they influence the price of properties with similar characteristics (Rosen, 1974).

I take into consideration only the observations after the end of the construction work as being post-policy ($Post_i = 1$) and drop observations between the start and end of the construction work (32,210 observations deleted) to prevent any anticipation effects from happening and ensure the aggregated effect of the price change is fully captured. As established the dataset goes from January 2018 to May 2024, which translates into having 4 years and 8 months of data in the pre-policy period, and 1 year after the GA are implemented, thus only short-term effects are observed.

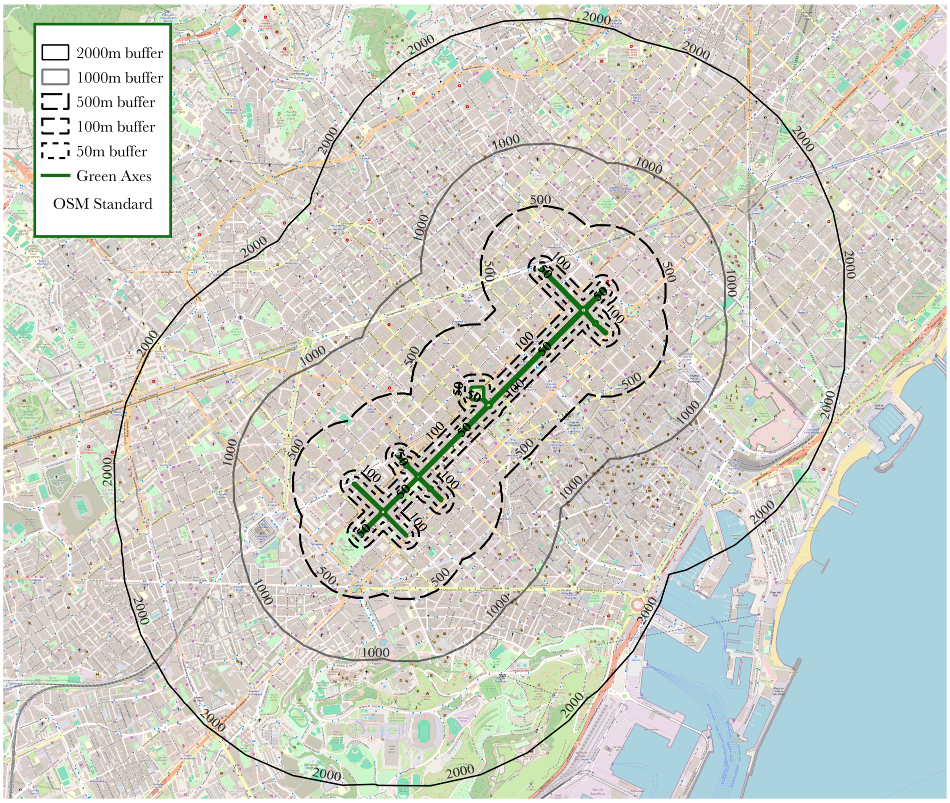

Figure 4: Map of Barcelona including the buffer areas for the treatment and control groups

<u>Definition of the treatment groups</u>

The buffer areas are illustrated in Figure 4, where the green lines represent the GA. As established, the distances of 50m, 100m and 500m are taken as reference for the treatment group. Firstly, I decided to use a 50m distance as the closest bound, that way the model allows us to see the effect on the directly adjacent apartments, being the ones that are most likely to be affected given the characteristics of the GA. On a relatable note, Jo Black and Richards (2020) use a treatment group at the 80m level, observing a high impact. Secondly, I use a 100m proximity band, as applied by Anguelovski et al. (2018) and Kang and Cervero (2009). In this case, 100m has an additional value since it is approximately the distance of a block of houses of the Eixample, which measures 113m, thus becoming a natural bound. Finally, I use a 500m proximity radius, to capture the aggregated effect at the 15-minute walking distance[29], which is a standard approach in the literature (Magrinyà et al., 2023). Previous studies suggest the impact of a greenway reaches its maximum for properties that are within 400m, implying housing value only decreases after 500m (Campbell and Munroe, 2007; Noh, 2019). Furthermore, the GA are relatively small-scale interventions and contain relatively little greenery if compared to North European or American parks where most of the existing literature is focused on. As a result, apartments that capitalize on GA are likely to be within close walking distance.

Definition of the control group

Thirdly, also represented in Figure 4, for the control group only observations that are between 2000m and 6000m away from the GA are used in the main approach, that is to ensure the control group is sufficiently far away so that no potential effect of the treatment is passed on to the control group. In Section 8, alternative control groups are used at 500m and 1000m. To determine the control group I rely on a regression applying the HP method, which gives a clear approximation of the area of influence of the GA on rental prices, which allows me to maximize the use of data to ensure a more robust estimation. The extent of the impact is estimated to be 2433m. Section 4.2.1 explains this procedure in more detail. Additionally, there is substantial literature on the extent of the effect of UGS on property value, nonetheless, there is no consensus, suggesting a range between 300m to 3000m. For instance, Jo Black and Richards (2020) use observations from 80m to 800m as control. Yu et al. (2020) find the influencing distance of a UGS in Shenzhen, China, to be 345m. In Yu et al. (2024) working paper, uses the area beyond 800m as the control for their study. As a final note, Liu et al. (2024a,b) find that the capitalization of green amenities is still substantial between 500m and 1000m, and can expand as far as 2000m, which is also corroborated by Melichar and Kaprová (2013). In an even more extreme case, Jun and Kim (2017) use a control between 3.6km and 5km to prevent spillovers.

4.2.1 Hedonic Pricing (HP) model

Here HP analysis is conducted. I use a non-linear approach by including the $Distance_i^2$. Although this method has limitations, has been widely used in the literature, Brander and Koetse (2011), Chen and Jim (2006), Kong et al. (2007), Kovacs (2012), Melichar and Kaprová (2013), Morancho (2003), Liebelt et al. (2018b), and Liu et al. (2024a,b) are some examples of it. How-

[29] This standard has been agreed upon by academics worldwide. It has been recognized that a 15-minute walk is a distance most people are willing to do by foot, and that enables citizens to fully endorse their surroundings. The 15-minute bound has been defined by the walking peace of $2km/h$, which is the one of an elderly or a child, and has been used to define the 15-minute city concept (Magrinyà et al., 2023).

ever, it will allow me to define the area of influence to apply the DiD strategy appropriately, preventing the control group from capitalizing on the new green infrastructure, and adjusting it to maximize data use. The regression is represented in Equation (2).

$$ln(Price_i) = \alpha + \beta_1 Distance_i + \beta_2 Distance_i^2 + \phi_t + \phi_l + \gamma X_i + \mu_i \quad (2)$$

Here, I define $ln(Price)$ as the dependent variable given that is the one used in the main approach. The independent variable is the distance from the GA ($Distance_i$), which is a continuous variable, together with the distance squared ($Distance_i^2$) to account for non-linear behaviour. Both effects are captured by β_1 and β_2 respectively. Time fixed effects, ϕ_t, and locational fixed effects, ϕ_l, are incorporated, together with controls for house characteristics, X_i, captured by γ. Finally μ_i represents the error term. Notice that the regression is run twice, before the implementation of the GA (data until the 15th of August of 2022), and after the implementation of the GA (data from 30th April 2023). We are interested in the post-policy period since it captures the value attributed to the GA, the pre-period is run to ensure the apartments adjacent to the treated streets were not already significantly more expensive.

Table 2: Hedonic Pricing Regression with Before and After

	Pre-policy	Post-policy
Distance	-0.0000281	-0.0000803**
	(0.0000200)	(0.0000382)
$Distance^2$	7.23e-09	1.65e-08*
	(6.36e-09)	(9.77e-09)
Fixed Effects	YES	YES
Descriptive controls	YES	YES
Observations	411199	41580

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2 presents the estimates of Equation (2). The coefficient for $Distance_i$ informs about the marginal effect, which as expected, is negative, suggesting that for each meter of distance gained from the GA, the monthly rent price decreases. Before the GA construction, the coefficient is non-significant. Conversely, in the post-policy period the coefficient suggests that for an apartment that is 1000m away from the GA, rent is 8.06% lower relative to an apartment that is directly by the GA. Additionally, the $Distance^2$ informs about the curvature of the function, in this case, it is positive and significant at 10% level, drawing a convex shape. That indicates that the marginal capitalization effect diminishes with distance, going from negative 8.06% per additional 1000m for apartments right by the GA, to negative 7.87% per 1000m additional meters for apartments 100m away from the GA. By using β_1 and β_2 I can compute the approximate distance of impact on rentals.

$$\frac{\delta Price}{\delta Distance} = -0.0000803 + 2 \times Distance \times 0.0000000165 = 0.$$

$$Distance = \frac{0.0000803}{2 \times 0.0000000165} = 2,433.33$$

The distance of impact is roughly 2,433m. Although it is a high value, it lies within the high end of the existing literature. This effect is likely to be overestimated due to OVB[30], confounders are likely since the Eixample has additional characteristics that might inflate rental prices, such as being a central neighbourhood. Notice that the coefficients pre-policy, although not significant, already suggest potential bias. Nevertheless, by using 2000m to 6000m from the GA as the control I ensure that spillover effects on the control group are minimal.

5 Parallel trends

Testing for parallel trends is crucial. In this section, Figure 5 and Table 3 (Section 5.1), are presented to illustrate the price trends from both groups. Figure 5 shows the treatment and control groups follow a similar pattern. By using a control group from the same city it is more likely that the parallel trends assumption is fulfilled. The black solid line represents the control group, and the dashed line represents the treatment group at 100m. The difference between the two lines stayed relatively stable over time, with some tightening after the eighth month of 2020, where rent prices dropped temporarily as a consequence of the implementation of the *Catalan Law of Rent Regulation* in September 2020, which was active until March 2022. Nonetheless, after April 2021, we see an upward trend in both groups. Notice that the grey vertical lines represent the time cutoffs, with the grey dashed line marking the beginning of the construction work and the solid grey line the end of it. After May of 2023, the difference in price between both groups has visibly increased. At the beginning of 2024, it appears to normalize again. The *Law on the Right to Property,* introduced in March 2024, might have played a part. Nonetheless, given the nature of the data, there are fewer observations in the year 2024, which explains the increased variation in this period.

[30] Omitted Variable Bias.

Figure 5: Parallel Trends graph at 100m treatment and 2000m to 6000m control ($ln(Price)$)

5.1 Formal test for parallel trends

This subsection aims to provide reliability to the results of this study and offer further robustness checks, other than Figure 5, proving that the pre-trends of both groups are statistically identical. A commonly used strategy is to regress the outcomes on pre-policy period dummies by interacting them with the treatment dummy.

$$ln(RentalPrice_i) = \alpha + \beta_1 Treatment_i + \beta_2 Quarter_i + \beta_3 (Treatment_i \times Quarter_i) + \mu_i \quad (3)$$

Formally, Equation (3) has been estimated, where $Treatment_i \times Quarter_i$ is the set of interactions between quarter-specific dummies and treatment dummies. The pre-policy period goes from the 1st quarter of 2018 to the 2nd quarter of 2022. The period between the 3rd quarter of 2022 to the 2nd quarter of 2023, corresponds to the construction period. The 2nd quarter of 2022 has been taken as the reference period since it is the last period before construction work started. For the outcome variables, 4 variables of interest are considered: $ln(Price)$, $Price$, $ln(UnitPrice)$, and $UnitPrice$.

Table 3 shows no significant differences in the outcome variables between treatment and control groups at the quarterly level for periods around the cutoff date, proving fulfilment of parallel trends and absence of anticipation effects. The results are generally satisfactory, largely showing no statistical difference in trends between the control and treatment group on $ln(Price)$, which is the chosen dependent variable in the main analysis. Between the 3rd quarter of 2020 and the 2nd quarter of 2021, estimates become significant, which coincides with the *Catalan Rent Control Legislation* being introduced. This is mostly observed for $Price$, $ln(UnitPrice)$ and $UnitPrice$. Nonetheless, the test does not show any signs of non-parallel trends for the quarters close to the start of the construction work date, and that is true for all outcome variables except $Price$ and $ln(UnitPrice)$, which show significance at 10% and 5% three quarters before the construction work started. Additionally, Table 3 informs about potential anticipation effects, Noh (2019) observed a 3.27% annual increase as it got closer to the opening date of the greenway in Whittier, California, nonetheless, that is not the case in this study. By looking into the estimates of quarters after the 3rd quarter of 2022, we see that for all outcomes the interactions show coefficients remain insignificant until the 2nd and 3rd quarter of 2023, which is when the GA were finished. This further validates the study by presenting evidence of no observable price increases during construction work. This is endorsed by the findings in Section 8. Two factors potentially explain the absence of anticipation effects, the first is the political uncertainty and long-time planning of the GA by the City Council, and the second is the nature of tenants who might not be staying long-term and don't benefit from the GA until they are finished, probably also having to endure a loud construction noise.

Nonetheless, although the coefficients remain insignificant, they become increasingly positive after the 1st quarter of 2023, justifying the exclusion of the 4th quarter of 2022 and the first quarter of 2023 from the main analysis, corresponding to the dates between the 15th of August of 2022 and the 30th of April of 2023, as has been done.

Table 3: Parallel Trends at 100m treatment and 2000m to 6000m control - 2q2022 as reference

	ln(Price)	*Price*	*ln(UnitPrice)*	*UnitPrice*
Treat100m×1q2018	0.0134	23.36	0.0160	0.177
	(0.0311)	(50.98)	(0.0187)	(0.315)
Treat100m×2q2018	0.0394	51.94	0.0322	0.422
	(0.0261)	(41.94)	(0.0255)	(0.430)
Treat100m×3q2018	0.0402	57.85	0.0314	0.413
	(0.0271)	(39.45)	(0.0195)	(0.417)
Treat100m×4q2018	0.0262	32.49	0.0618**	1.078**
	(0.0305)	(43.02)	(0.0271)	(0.495)
Treat100m×1q2019	0.0163	31.57	0.00292	0.174
	(0.0328)	(47.55)	(0.0362)	(0.601)
Treat100m×2q2019	-0.0484	-60.60	0.0108	0.0189
	(0.0335)	(49.92)	(0.0218)	(0.348)
Treat100m×3q2019	-0.0283	-25.29	-0.0244	-0.412
	(0.0311)	(47.94)	(0.0282)	(0.512)
Treat100m×4q2019	-0.00559	-2.948	-0.00742	-0.181
	(0.0357)	(54.11)	(0.0250)	(0.392)
Treat100m×1q2020	-0.0212	-3.501	-0.00930	-0.154
	(0.0436)	(71.86)	(0.0267)	(0.442)
Treat100m×2q2020	-0.0542*	-58.17	-0.0420**	-0.843**
	(0.0307)	(44.28)	(0.0174)	(0.365)
Treat100m×3q2020	-0.00719	13.22	-0.0250	-0.372
	(0.0397)	(67.84)	(0.0236)	(0.472)
Treat100m×4q2020	-0.0505*	-81.78**	-0.0725***	-1.367***
	(0.0302)	(41.31)	(0.0184)	(0.415)
Treat100m×1q2021	-0.0524*	-89.21**	-0.0593***	-1.226***
	(0.0280)	(43.38)	(0.0198)	(0.428)
Treat100m×2q2021	-0.0111	-24.93	-0.0111	-0.333
	(0.0280)	(40.71)	(0.0200)	(0.316)
Treat100m×3q2021	-0.0432	-75.70**	-0.0357*	-0.750
	(0.0275)	(38.10)	(0.0206)	(0.462)
Treat100m×4q2021	-0.000417	-18.66	-0.000503	-0.0968
	(0.0313)	(48.01)	(0.0257)	(0.404)
Treat100m×1q2022	0.00743	2.792	-0.0133	-0.240
	(0.0297)	(45.05)	(0.0179)	(0.318)
Treat100m×2q2022	0	0	0	0
	(.)	(.)	(.)	(.)
Treat100m×3q2022	0.0234	56.65	0.0458	1.136*
	(0.0428)	(74.10)	(0.0280)	(0.616)
Treat100m×4q2022	0.0219	53.33	0.0381	0.837
	(0.0347)	(56.18)	(0.0282)	(0.561)
Treat100m×1q2023	0.0227	47.08	0.0397*	0.914**
	(0.0269)	(43.65)	(0.0202)	(0.431)
Treat100m×2q2023	0.0743*	179.5**	0.0734**	1.807***
	(0.0410)	(77.50)	(0.0287)	(0.678)
Treat100m×3q2023	0.0821**	180.7***	0.0384	1.157*
	(0.0352)	(64.27)	(0.0283)	(0.633)
Outliers	NO	NO	NO	NO
Observations	165483	165483	165483	165483

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6 Main results

In this section, I present the results for the main DiD regression showing statistically significant positive coefficients. In addition to Equation (1), I include Equation (4), a simplified version which excludes the fixed effects (ϕ_t and ϕ_l) and the descriptive controls (X_i) to illustrate how the coefficients are affected by their inclusion. Nonetheless, the analysis will be focused on the main regression.

$$ln(RentalPrice_{it}) = \alpha + \beta_1 Treatment_i + \beta_2 Post_i + \beta_3 (Treatment_i \times Post_i) + \mu_{it} \quad (4)$$

Table 4, presents results that are statistically and economically significant at 1% level at all distances for both models. The results suggest that the area around the transformed streets was already more expensive, nonetheless, prices increased even more as a consequence of the GA implementation. Columns 1 and 2 show more moderate coefficients compared to columns 4 and 5. That is not the case for the 500m estimates in columns 3 and 6. This indicates that the inclusion of controls improved the model by controlling for confounders. The simple model suggests a convex marginal effect, with prices rising more for apartments further away from the GA.

Table 4: Main DiD regression at 50m, 100m, and 500m with 2000m to 6000m control ($ln(Price)$)

	Simple		—	Main Regression		
	50m	100m	500m	50m	100m	500m
Treat m	0.159***	0.157***	0.137***	0.164***	0.154***	0.116***
	(0.0593)	(0.0551)	(0.0383)	(0.0130)	(0.0129)	(0.00324)
PostEnd	0.154***	0.154***	0.154***	0.237***	0.236***	0.0166**
	(0.00862)	(0.00862)	(0.00862)	(0.00445)	(0.00436)	(0.00830)
Treat m × PostEnd	0.0512**	0.0673***	0.0764***	0.141***	0.0811***	0.0390***
	(0.0209)	(0.0146)	(0.0172)	(0.0102)	(0.00495)	(0.00594)
Fixed effects	NO	NO	NO	YES	YES	YES
Descriptive controls	NO	NO	NO	YES	YES	YES
Observations	146876	154507	218940	138253	145364	205415

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Focusing on the last three columns, for the treatment group within 50m of the main DiD model, β_3 implies a 15.14% increase as a consequence of the GA construction. Notice that log-linear interpretation of the coefficient implies $(e^{0.141} - 1) \times 100$. On the same line, the treatment group for those observations within 100m suggests an 8.45% increase in the rental price. Finally, within 500m the increase is less steep although still significant at the 1% level, with a 3.98% increase, due to apartments being less affected as they get further away from the transformed streets. Those results are in line with the literature, and although rent prices are typically less responsive than sale prices, tenants bear considerably the price aggravation in this case, with an increase higher than the 8.2% found by Piaggio (2021). These results resemble the literature on sale prices that showed coefficients of 10.85% (Noh, 2019), 17.2% (Chen and Jim 2022), and 20% (Bockarjova et al., 2020). A possible explanation for such results is their central location of the GA, in addition to the lack of green spaces in Barcelona and the increasing demand for rental apartments in the city, prompting a higher marginal value on green amenities. On those lines, Zambrano-Montserrate et al. (2021) suggest small forests within the city centre are more valuable because are closer to a higher number of citizens. To put this into perspective, the average rent of apartments within 50m before the application of the policy is 1436.79€, thus a 15.14% increase supposes an average increment of 217.53€ in monthly rent, which is equivalent to 2610.36€ annually. Following the same procedure, the estimated increase for apartments within 100m is of 121.21€ per month increase and 57.10€ for those within 500m.

7 Heterogeneity at floor levels

In this section, I present evidence of heterogeneous increases in prices depending on the floor level at which the apartment is found for the 50m, 100m, and 500m treatment groups. Jo Black and Richards (2020) find that vertical proximity to green spaces has an effect on prices, as mentioned in Section 2. I conducted an additional heterogeneity analysis to test potential differential coefficients depending on vertical proximity to the GA. Using $floorlevel$ I created three groups, Low (floor levels: 0, 1, 2, and 3), Mid (floor levels 4, 5, 6, and 7), and $High$ (floor levels 8, 9, 10, and 11). To make the interpretation easier $High$ is taken as the reference floor, thus the coefficients of Low and Mid are relative to the $High$ level. The equation below shows the regression, which follows the same form as Equation (1) but here the floor-level interaction term, $Level$ is included.

$$\begin{aligned}\ln(Price_i) = \alpha + \beta_1 Treatment_i + \beta_2 Post_i + \lambda Level_i + \beta_3(Treatment_i \times Post_i) \\ + \beta_4(Treatment_i \times Post_i \times Level_i) + \beta_5(Treatment_i \times Level_i) \\ + \beta_6(Post_i \times Level_i) + \phi_t + \phi_l + \gamma X_i + \mu_i\end{aligned} \tag{5}$$

The results of the regression are presented in Table 5. The effect is captured by the interaction term $Treatment_i \times Post_i \times Level_i$ and represented by β_4. Notice that the results presented in this case use 1000m to 6000m distance as the control area. The model has also been tested using the 2000m to 6000m control which shows less significant results and an increased heterogeneity of prices at floor levels as distance from GA is gained, presented in the Appendix (Table 12).

Table 5: Heterogeneity test DiD regression, showing *Low* and *Mid* floor level effect ($ln(Price)$)

	50m	100m	500m
Treat m	0.0262	0.00769	0.0215
	(0.0186)	(0.0152)	(0.0141)
PostEnd	0.168***	0.168***	0.168***
	(0.00714)	(0.00713)	(0.00707)
Treat m×PostEnd	0.139***	0.125***	-0.0617*
	(0.0167)	(0.0181)	(0.0327)
Low	-0.0497***	-0.0500***	-0.0506***
	(0.00560)	(0.00560)	(0.00558)
Low×PostEnd	-0.00971	-0.00969	-0.00989
	(0.00737)	(0.00737)	(0.00734)
Low×Treat m	-0.0249	-0.0181	-0.0137
	(0.0186)	(0.0163)	(0.0116)
Treat m×PostEnd×Low	0.0465**	0.0363	0.0442**
	(0.0215)	(0.0224)	(0.0187)
Mid	-0.0369***	-0.0370***	-0.0374***
	(0.00517)	(0.00517)	(0.00516)
Mid×PostEnd	-0.00123	-0.00125	-0.00169
	(0.00699)	(0.00698)	(0.00695)
Mid×Treat m	-0.0268	-0.0228	-0.0216*
	(0.0224)	(0.0188)	(0.0121)
Treat m×PostEnd×Mid	0.0391**	0.0489***	0.0448***
	(0.0189)	(0.0183)	(0.0148)
Fixed effects	YES	YES	YES
Descriptive controls	YES	YES	YES
Observations	292312	299423	359474

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5 results are revealing, showing that *Low* and *Mid* are less valued overall, nonetheless the interaction term indicates a higher price change for low- and mid-floor apartments relative to those on the top floors as a result of green street infrastructure. All coefficients of interest, β_4, are significant except in the case of *Low* level at 100m. We see an increase over 4.5%[31] for *Low* and *Mid* apartments overall, relative to *High* level apartments. Interestingly, those results stay true for apartments within 500m. It would be expected to observe a more homogeneous impact across floor levels as observations gain distance from the GA, since differential benefits,

[31] Results suggest a 4.76% increase for low-floor apartments at 50m and a 4.52% increase for 500m. And in the case of mid-floor apartments a 3.99%, 5.01%, and 4.49% for 50m, 100m, and 500m respectively.

most likely coming from noise reduction, are unlikely for apartments after the 100m mark. Nonetheless, $High$ being already more expensive might leave less room for increasing the prices of the apartments high-floor apartments.

8 Sensitivity analysis

In this section, I conduct robustness checks in order to further test the reliability of the estimates to ensure that the assumptions made in the main analysis do not drive the results. Evidence will be provided for coefficients distances between 1000m and 6000m as control groups, using July 2023 as the cutoff, data including outliers, using three alternative outcome variables, and further testing for a potential anticipation effect during construction work.

8.1 Control distance at 500m and 1000m

In the first place, I test the model for adjusted control groups, using the distance brackets between 500m and 6000m and 1000m and 6000m. Throughout the analysis, the bracket between 2000m and 6000m has been used as the comparison since that is what the HP model suggested.

The results presented in Table 6, using Equation (1), indicate that there is spillover effects between 500m and 1000m, but past 1000m they are rather unlikely. The estimates for the 500m to 1000m control group show no significance, however, for the 1000m to 6000m bracket they show a substantial increase in rent for apartments within 100m, being statistically significant at 1% level. Both new control groups secure slightly improved parallel trends, which have been tested for[32]. The fourth column displays the results for the treatment group within 50m, given the log-linear approach, the interaction term suggests a 23,74% increase as a consequence of the GA construction. On the same line, the treatment group for those observations within 100m shows a 17.94% increase post-policy. Conversely to what was found in the main analysis, results for 500m are non-significant, suggesting a much steeper decrease of the GA premium as they get further away.

These results are much higher than the ones in Table 4, which can be interpreted as the lower bound. The cause of the difference in estimates between these two approaches might be explained by the more robust parallel trends at 1000m (see Appendix Table 13) compared to 2000m, nonetheless, this remains to be better understood.

[32]see Appendix Table 13.

Table 6: DiD regression at 50m, 100m, and 500m decreasing the control band at 500m and 1000m ($ln(Price)$)

	500m to 6000m control			1000m to 6000m control		
	50m	100m	500m	50m	100m	500m
Treat m	0.000353	-0.00841	0.00746	-0.000538	-0.0149***	0.00549
	(0.0176)	(0.0149)	(0.00763)	(0.00381)	(0.00330)	(0.0101)
PostEnd	0.162***	0.162***	0.161***	0.162***	0.162***	0.162***
	(0.00122)	(0.00121)	(0.00117)	(0.00145)	(0.00143)	(0.00135)
Treat$m$ × PostEnd	-0.0417	0.0326	0.0211	0.213***	0.165***	-0.0227
	(0.0860)	(0.0316)	(0.0160)	(0.00569)	(0.00348)	(0.0302)
Fixed effects	YES	YES	YES	YES	YES	YES
Descriptive controls	YES	YES	YES	YES	YES	YES
Observations	392193	399304	459355	292312	299423	359474

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

8.2 Adjusting end date to July 2023

Secondly, I provide more evidence of the adequacy of the suitability of the chosen cutoff dates. The change of government mid-construction led to some delays, thus, although most of the work was already done by the 30th of April of 2024, there might have been some pending final adjustments. The new City Council announced that work was definitely finished by July 2023. Using April helped secure a higher number of observations for the post-policy, but might have led to some bias. As a result, I use Equation (1) and adjust the post-treatment variable. As it can be observed in Table 7, the results remain exactly the same as with the original cutoff date.

Table 7: DiD regression with 5th July 2023 as the cutoff date, at 50m, 100m, and 500m, control at 2000m to 6000m ($ln(Price)$)

	50m	100m	500m
Treat m	0.165***	0.155***	0.116***
	(0.0130)	(0.0129)	(0.00329)
PostJuly	0.236***	0.236***	0.0264**
	(0.00448)	(0.00440)	(0.0102)
Treat m × PostJuly	0.142***	0.0815***	0.0298***
	(0.0104)	(0.00504)	(0.00813)
Fixed effects	YES	YES	YES
Descriptive controls	YES	YES	YES
Observations	135101	142029	200676

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

8.3 Outliers

Thirdly, to provide a better understanding of the part played by outliers, in Table 8 I show the estimates before outliers were deleted. I used the standard approach with Equation (1).

Table 8: DiD regression containing outliers, at 50m, 100m, and 500m and 2000m to 6000m as control ($ln(Price)$)

	50m	100m	500m
Treat m	0.275***	0.267***	0.106***
	(0.0201)	(0.0193)	(0.00475)
PostEnd	0.209***	0.208***	0.0384***
	(0.00626)	(0.00620)	(0.00916)
Treat m×PostEnd	0.282***	0.145***	0.0258***
	(0.0117)	(0.00681)	(0.00636)
Outliers	YES	YES	YES
Fixed effects	YES	YES	YES
Descriptive controls	YES	YES	YES
Observations	146586	154047	217074

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As can be seen, the number of observations does not vary significantly, nonetheless, the coefficients do. If we focus on the interaction term, the presence of outliers increases the estimate up to 32.58% (50m) and 15.60% (100m) compared to the 15.14% and 8.45% with the clean database respectively. Notice that the 500m band presents a more moderate estimate, 2.61%, compared to the 3.98% in the main analysis. Two potential factors drive these results. On the one hand, given the area established as treated is relatively small (within 100m), the number of treated apartments post-policy is lower than in the control group post-policy, thus more sensitive to outliers. On the other hand, outliers are more predominant in the treated group post-policy, which might indicate a rise in high-end apartments in this area. Liu et al. (2024b) find high-end apartments experience growth along greenways, thus being a potential explanation for the observed differences in coefficients. This further stresses the estimates found, which I argue represent the lower bound.

8.4 Alternative outcomes

Fourthly, I run the DiD regression at the 100m treatment level, for four different outcome variables: $ln(Price)$, $Price$, $ln(UnitPrice)$, and $UnitPrice$. This offers alternative dependent variables to see if the results hold. Table 9 shows that, although more moderate for $/m^2$, results maintain the level of statistical significance. Looking at the $UnitPrice$ coefficient, a 4.37% increase is observed, which supposes a 0.71€ per m^2 if the monthly average rent per square metre before the GA were implemented is used (16.3€/m^2), which is smaller than the $UnitPrice$ estimate of 1.67€/m^2. For an 80 m^2 apartment, 1.67€/m^2 supposes approximately 57€ of additional monthly rent, which is lower than the increase found with the $ln(Price)$ and $Price$, which are 121.21€ and 203.4€ respectively. Overall outcomes using /m^2 suggest an increase at the 100m radius more on the lines of the literature (see Section 2).

Table 9: DiD regression at 100m and control from 2000m to 6000m using $ln(Price)$, $ln(UnitPrice)$, $Price$ and $UnitPrice$ as dependent variables.

	ln(Price)	ln(UnitPrice)	Price	UnitPrice
Treat100m	0.154***	0.0589***	110.4***	0.993***
	(0.0129)	(0.0118)	(19.18)	(0.212)
PostEnd	0.236***	0.235***	303.2***	3.384***
	(0.00436)	(0.00504)	(8.760)	(0.0817)
Treat100m × PostEnd	0.0811***	0.0428***	203.9***	1.673***
	(0.00495)	(0.00547)	(9.168)	(0.0915)
Fixed effects	YES	YES	YES	YES
Descriptive controls	YES	YES	YES	YES
Observations	145364	145364	145364	145364

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

8.5 Effect during construction

It is also interesting to study the increase in prices as a consequence of the start of construction work. Also following Equation (1), instead of using the end of construction work as the cutoff date, I use the date of the start of construction to create a dummy $PostConstruction_i$ that equals 1 for those rentals observed during the construction work (between 15th August 2022 and 30th of April 2023). Table 10 presents the estimates in the same format as Table 4. The results show no significant negative estimates. That is not common in the literature, since property prices usually anticipate policy implementations, adjusting the price beforehand. As addressed in Section 5. There are two potential hypotheses to justify it. First, tenants only benefit from locational amenities in the short term depending on the extent of their contract, thus they might not be so willing to pay a higher price before the construction work is finished. Secondly, construction work is a disamenity which renters have to endure, limiting access to their homes and increasing noise during the day. In any case, the fact that rent prices are held stable until GA is terminated validates, even more, the estimates in Table 4.

Table 10: DiD looking effect during construction. Treatment at 50m, 100m, and 500m and control from 2000 to 6000m.

	(50m)	(100m)	(500m)
Treat m	-0.000409	-0.0130*	0.120***
	(0.00692)	(0.00706)	(0.00316)
PostConstruction	0.0267***	0.0268***	0.0264***
	(0.00472)	(0.00470)	(0.00466)
Treat m × PostConstruction	-0.00640	-0.00519	-0.00419
	(0.0140)	(0.0107)	(0.00632)
Fixed effects	YES	YES	YES
Descriptive controls	YES	YES	YES
Observations	148469	156029	220113

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

9 Discussion and limitations

This study provides strong evidence of the capitalization of green urban interventions on rental prices, specifically focusing on the Green Axes (GA) project in the Eixample district of Barcelona. While the results indicate a positive impact on nearby rents, there are several limitations and contextual factors that must be considered when interpreting the findings.

One limitation relates to the use of advertised rental prices rather than final transaction prices. Although prior studies suggest that the difference between the two is minimal for rentals Liu et al. (2024b), it is important to acknowledge that advertised prices may not always reflect the final price paid by tenants, potentially leading to a slight overestimation in the results.

Furthermore, the scope of the analysis was restricted to aggregated data across all Green Axes, which may have masked heterogeneity in the effects between different axes. Avinguda Diagonal, Via Laietana, Glòries, and Les Rambles, underwent simultaneous urban transformations to the GA that could have influenced rental prices. However, this study treated these sections as part of the control group, which might have introduced a downward bias in the results. Future research could focus on isolating the effects of individual axes for a more granular analysis.

Another potential limitation is the influence of the *Catalan Law of Rent Contention* (*Llei de Contenció dels Lloguers*), which was in effect from September 2020 until March 2022, in addition to the Law of the Right to Property introduced in March 2024. While these laws aimed to cap rental prices across Barcelona affecting both, treatment and control groups. Nonetheless, it is crucial to recognize that the general rental market during the study period was under this regulatory pressure.

The study also had to exclude key housing characteristics like terraces, gardens, and pools due to missing data. These omissions could lead to omitted variable bias, as such amenities are likely to significantly influence rental prices.

The timeframe for the post-treatment period was relatively short, spanning from April 2023 to June 2024. The long-term effects of green urban interventions often differ from short-term impacts, as shown in other studies that document a decrease in the premium over time (Anguelovski et al., 2018). Therefore, the results here represent short-term impacts and may not fully capture potential future price adjustments.

Lastly, the study's geographic scope was limited to a specific high-density urban environment. This focus provides valuable insights into the effect of green urbanization in similar cities, but results may not be generalizable to areas with different urban structures or socio-economic contexts.

10 Conclusion and policy implications

This paper analyzes the impact of the GA construction in Barcelona's Eixample district on nearby apartment rental prices, finding significantly positive results, which should be interpreted as the lower bound. Apartments on lower and mid-floor levels are particularly affected by the GA. Robustness checks confirm the reliability of these findings.

The main results show a 15.14% increase in monthly rent for apartments within 50m of the GA, 8.45% for those within 100m, and 3.98% for those within 500m. These increases are higher than the ones in the previous literature, raising concerns about social stability. Resulting in increases of 217.53€ (50m), 121.21€ (100m), and 57.10€ (500m). Additionally, lower and mid-floor apartments experience a 4.5% higher rent increase across all distances compared to higher-floor apartments.

Several sensitivity tests reinforce these conclusions. Adjusting the control group distance to 1000m revealed even steeper effects, with coefficients of 23.74% (50m) and 17.94% (100m), approaching the 31% price *green premium* observed around other UGS in Barcelona (Anguelovski et al., 2018). While the HP model suggests an area of influence up to 2400m, the effect significantly diminishes after 500m. The strong price increases are arguably caused by Barcelona's constrained rental market, high living costs, and dense population with limited green spaces. Furthermore, due to tenants' behaviour, rent prices produce a clearer cut between pre- and post-GA implementation leading to negligible anticipation effects.

These results provide clear evidence of the capitalization of green amenities by private owners, most notably around the 100m buffer, which raises concerns about green gentrification. As noted by Cui et al. (2018) and Zambrano-Monserrate et al. (2021), lower-income residents are less likely to tolerate rent increases as a result of green spaces, making them more vulnerable to displacement. While the health and quality-of-life improvements from urban greening are undeniable, as found by Bockarjova et al. (2020), Mueller et al. (2021), Opbroek et al. (2024), and Palencia et al. (2021), the evidence supports the need for accompanying socially responsible rent control measures, as advocated by Anguelovski et al. (2018), Bockarjova (2020), and Hochstenbach and Musterd (2018), to mitigate the social inequalities that might stem from green urban planning.

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11 Appendix

11.1 DiD regression at 100m treatment and 2000m to 6000m control, including coefficients for covariates

Table 11: DiD regression at 100m treatment and 2000m to 6000m control, including coefficients for all covariates ($ln(Price)$)

	100m
	100m
Treat 100m	0.154***
	(0.0129)
PostEnd	0.236***
	(0.00436)
Treat 100m×PostEnd	0.0811***
	(0.00495)
Year 2018	0
	(.)
Year 2019	0.0618***
	(0.00364)
Year 2020	-0.0232***
	(0.00295)
Year 2021	-0.0805***
	(0.00236)
Year 2022	-0.00990***
	(0.00376)
Year 2023	0.0913***
	(0.00306)
$m2$	0.00641***
	(0.000158)
$lift$	0.0510***
	(0.00783)
Flat location Interior	-0.0389***
	(0.00714)
0 floor level	-0.0172***
	(0.00635)
1st floor level	-0.0281***
	(0.00487)

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	100m
2st floor level	0
	(.)
3rd floor level	0.00184
	(0.00422)
4th floor level	0.0125**
	(0.00491)
5th floor level	0.0183***
	(0.00560)
6th floor level	0.0262***
	(0.00665)
7th floor level	0.0239***
	(0.00605)
8th floor level	0.0442***
	(0.00864)
9th floor level	0.0689***
	(0.0101)
10th floor level	0.0606***
	(0.0143)
11th floor level	0.0735***
	(0.0151)
New apartment	0
	(.)
To be restored	-0.214***
	(0.0731)
Good condition	-0.146**
	(0.0721)
Temporary rental	0.145***
	(0.00704)
Vacation rental	0.0663***
	(0.00803)
0 Rooms	0
	(.)
1 Room	0.0476***
	(0.00912)
2 Rooms	0.0910***
	(0.0105)

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	100m
3 Rooms	0.0598***
	(0.0117)
4 Rooms	0.0241*
	(0.0128)
5 Rooms	-0.0580**
	(0.0269)
6 Rooms	-0.0210
	(0.0513)
0 Bathrooms	0
	(.)
1 Bathroom	0.205***
	(0.0466)
2 Bathrooms	0.315***
	(0.0488)
3 Bathrooms	0.353***
	(0.0512)
4 Bathrooms	0.360***
	(0.0549)
5 Bathrooms	0.367***
	(0.0614)
Outliers	NO
Observations	145364

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

11.2 Heterogeneity at floor levels using 2000m to 6000m control

Table 12: 2000 Heterogeneity test DiD regression, showing *Low* and *Mid* floor level effect ($ln(Price)$)

	50m	100m	500m
Treat m	0.198***	0.183***	0.131***
	(0.0225)	(0.0197)	(0.0124)
PostEnd	0.223***	0.223***	0.00645
	(0.00892)	(0.00886)	(0.0106)
Treat m×PostEnd	0.0847***	0.0606***	0.00847
	(0.0178)	(0.0194)	(0.0175)
Low	-0.0584***	-0.0587***	-0.0591***
	(0.00783)	(0.00782)	(0.00791)
Low×PostEnd	0.00258	0.00273	0.00303
	(0.00977)	(0.00976)	(0.00979)
Low×Treat m	-0.0176	-0.0108	-0.00764
	(0.0199)	(0.0175)	(0.0130)
Treat m×PostEnd×Low	0.0356	0.0237	0.0326*
	(0.0219)	(0.0232)	(0.0197)
Mid	-0.0361***	-0.0364***	-0.0368***
	(0.00815)	(0.00815)	(0.00822)
Mid×PostEnd	0.0123	0.0124	0.0122
	(0.0101)	(0.0101)	(0.0101)
Mid×Treat m	-0.0275	-0.0235	-0.0234*
	(0.0235)	(0.0199)	(0.0136)
Treat m×PostEnd×Mid	0.0274	0.0350*	0.0317*
	(0.0213)	(0.0203)	(0.0167)
Observations	138253	145364	205415

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

11.3 Parallel Trends Test for 1000m to 6000m control

Table 13: Parallel Trends at 100m treatment and 1000m to 6000m control - 2q2022 as reference

	$ln(Price)$	$Price$	$ln(UnitPrice)$	$UnitPrice$
Treat100m×1q2018	0.0103	22.35	-0.00181	-0.0928
	(0.0267)	(45.98)	(0.0168)	(0.273)
Treat100m×2q2018	0.0253	34.00	0.0316	0.427
	(0.0224)	(37.87)	(0.0227)	(0.384)
Treat100m×3q2018	0.0359	50.68	0.0368**	0.536
	(0.0238)	(34.85)	(0.0152)	(0.358)
Treat100m×4q2018	0.0446*	62.82*	0.0613**	1.099**
	(0.0265)	(37.16)	(0.0246)	(0.457)
Treat100m×1q2019	0.0149	27.91	0.00846	0.282
	(0.0291)	(42.75)	(0.0340)	(0.562)
Treat100m×2q2019	-0.0263	-29.19	0.0147	0.140
	(0.0294)	(45.01)	(0.0175)	(0.260)
Treat100m×3q2019	-0.0103	-2.087	-0.0172	-0.242
	(0.0274)	(41.95)	(0.0241)	(0.433)
Treat100m×4q2019	-0.00219	2.582	-0.00887	-0.178
	(0.0318)	(48.63)	(0.0212)	(0.313)
Treat100m×1q2020	0.00103	30.11	-0.00238	-0.0412
	(0.0399)	(66.95)	(0.0234)	(0.376)
Treat100m×2q2020	-0.0258	-21.04	-0.0161	-0.398
	(0.0255)	(37.79)	(0.0125)	(0.298)
Treat100m×3q2020	0.0138	36.08	-0.00203	-0.0272
	(0.0357)	(62.92)	(0.0209)	(0.430)
Treat100m×4q2020	-0.0233	-47.04	-0.0397***	-0.840**
	(0.0267)	(36.52)	(0.0147)	(0.372)
Treat100m×1q2021	-0.0211	-49.97	-0.0345**	-0.765*
	(0.0235)	(37.91)	(0.0166)	(0.391)
Treat100m×2q2021	0.00494	-5.207	0.00996	0.0649
	(0.0235)	(34.27)	(0.0168)	(0.256)
Treat100m×3q2021	-0.0230	-47.43*	-0.0154	-0.360
	(0.0210)	(28.54)	(0.0157)	(0.397)
Treat100m×4q2021	0.00282	-7.851	-0.00518	-0.178
	(0.0251)	(37.24)	(0.0237)	(0.366)
Treat100m×1q2022	0.0109	7.532	-0.0197	-0.397
	(0.0262)	(39.44)	(0.0159)	(0.284)
Treat100m×2q2022	0	0	0	0
	(.)	(.)	(.)	(.)
Treat100m×3q2022	0.00933	37.40	0.0356	0.922
	(0.0408)	(71.78)	(0.0262)	(0.592)
Treat100m×4q2022	0.00308	16.02	0.0198	0.391
	(0.0318)	(52.00)	(0.0265)	(0.540)
Treat100m×1q2023	0.00781	24.69	0.0198	0.482
	(0.0240)	(39.61)	(0.0193)	(0.423)
Outliers	NO	NO	NO	NO
Observations	341523	341523	341523	341523

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$