Universitat Autònoma de Barcelona

Facultat d'Economia i Empresa UAB

Analysing green gentrification in Madrid through a geographic regression discontinuity design

Júlia Martí Llobet
Bachelor Degree in Economics
Final Bachelor Thesis

Tutor: Jordi Caballé Vilella
Department of Economics and Economic History

May 2023

ACKNOWLEDGMENTS

I would like to thank all the people who, in one way or another, have contributed and helped me to write this thesis.

First of all, grateful gratitude to Jordi Caballé Vilella (PhD, Professor of Economics, Autonomous University of Barcelona), for being my tutor. For guiding me during the research and writing process and offering me all the time that was needed.

I would like to extend my sincere thanks to Till Wicker, Economics PhD-student at Tilburg University, for his kindness and humility since the first moment I talked to him. He has always supported and assisted me in any of my research's challenges.

Special thanks to Carolina Martí-Llambrich (PhD in Geography, specialised on Planning and Environmental Management at the University of Girona) for her invaluable guidance and support in the development and structuring of this paper.

Thanks should also go to Francesc Fusté-Forné (PhD, Department of Business, University of Girona) for his contribution throughout the entire development of my thesis, from its initial idea to the final day.

Also, I would like to express my deepest appreciation to Isabelle Anguelovski, director of Barcelona Laboratory for Urban Environmental Justice and Sustainability (BCNUEJ), for her valuable and expert suggestions and for her willingness to introduce me in the field of green gentrification.

And finally, I would also like to mention my friends and family, who have been with me every step of the way and have always believed in me.

To all of you, my deepest gratitude.

ABSTRACT

The benefits of municipal greening initiatives are increasingly at the centre of urban development strategies. However, some critical scholars have begun to question the neutrality of these projects, presenting evidence of green gentrification. In this study, I evaluate the impact of six green parks created between 2009 and 2015 in the city of Madrid, three and six years after their inauguration. I address my question using a Geographical Regression Discontinuity design (GRD), where treatment assignment is based on the distance from each neighbourhood's centroid to the closest park's boundary while considering adjacent neighbourhoods as valid counterfactuals. I examine seven socio-demographic and economic gentrification indicators in both treatment and control groups. I aim to establish a causal inference on creating new urban green amenities on the displacement of vulnerable and marginalized residents. My results do not indicate the existence of any gentrifying trend in the neighbourhoods under the study, but they suggest some insights that contribute to the current green gentrification literature.

Key words: green gentrification, green infrastructure, Madrid, Madrid Río, environmental justice.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

Current climate and health emergencies and the multiple socio-environmental challenges are increasingly at the centre of cities' development strategies and urban planning practices, as well as the difficulties involved with sustainability and justice integration. Green infrastructure in cities plays an important role here, and its contribution is visible in health, ecology, and social relations. Greenspaces improve air quality and moderate temperatures during hot periods, also providing shaded areas. Green amenities are also seen as a place for physical exercise and a meeting point for social interaction by promoting community cohesion and reducing social isolation for socially deprived communities and minority groups. The health benefits of green and blue spaces are numerous: reduction of mortality and morbidity from chronic diseases, as well as obesity and improvement of mental health. There is also growing evidence that exposure to greenspaces around the home triggers physical, emotional, and cognitive development in children (European Environment Agency, 2022).

Access to the benefits mentioned above may be unevenly distributed across the citizens. Only some people can benefit from green and blue amenities, and environmental justice appears at the core of urban sustainability's implementation. In the World Social Report 2020 (UNDESA, 2020), urbanization is listed in the top 4 trends society faces today, together with climate change, technological innovation, and international migration. It highlights the interconnection between environmental degradation and urban inequality and cities' critical role in carrying out climate responses combining resilience planning and adaptation plans. Climate impacts are more significant in economically and socially marginalized communities within big cities, and the efforts to fight against these effects further increase existing inequalities (Kotsila et al., 2023).

In 1987, the World Commission on Environment and Development (Brundtland Commission) promoted "sustainable development" in its report Our Common Future (United Nations, 1987). In turn, one of the main goals of the UN 2030 Agenda for Sustainable Development (2015) is urban development, including inclusion, security, resilience, and sustainable development. This concept's presence in both organizations' goals shows how sustainable urban development relates to achieving economic, environmental, and social goals following green, profitable, and fair practices.

This paper focuses on green gentrification, that is the demographic change that can take place in a disadvantaged or underinvested neighbourhood after an urban green project or infrastructure has been developed in that area. Making some disadvantaged neighbourhoods more climate resilient through any green infrastructure can increase the value of the area, and consequently, generate a demographic change towards wealthy and more educated households.

The main goal of this research is to find a causal effect of new green urban amenities on potential gentrification trends around them. Concretely, I study the impact of the creation of six different green parks in the city of Madrid inaugurated between 2009 and 2015 on seven socio-demographic and economic variables of the population in the nearby neighbourhoods: The percentage of people older than 65, the percentage of the population over 65 years old living alone, the percentage of the population with foreign nationality, the unemployment rate, the percentage of the population with high education, the annual real net household income and second-hand housing real prices. These are key variables that reflect gentrification and that are widely used in gentrification studies. To address the challenges of the research's aim, I undertook a Geographic Regression Discontinuity Design (GRD) by creating a treatment and a control group according to the distance from each neighbourhood's centroid to the closest park's boundary.

If green gentrification occurs, we should observe the following effects, or most of them, on the indicators I next enumerate to be able to establish a causal relationship:

1. A greater decrease in the percentage of the population over 65 living alone in those neighbourhoods near the park (treatment group) compared to the control group.
2. A more significant decrease in the percentage of the population with foreign nationality in the treatment group than in the control group.
3. A more considerable increase in the percentage of the population holding a bachelor's degree or other high education level in the treatment group than in the control group.
4. A significant increase in the annual real net household income of those living near the park compared to those located further away.
5. A greater increase in second-hand housing prices around the parks under analysis than further away.

I also introduce some covariates in my model as I believe that the magnitude of the treatment effect may vary across neighbourhoods, being more extensive and more harmful in more vulnerable and poor areas of the city; and that the growth of population or the baseline value of the variable of interest may influence my gentrification indicators. I also believe that the nearer the neighbourhood to the park, the stronger its effect on the socio-demographic and economic variables under the study.

The remainder of the paper has the following structure. Section 2 offers a theoretical framework of the concept of green gentrification together with a review of its existing literature. Section 3 justifies the geographical area of our analysis, Madrid. Section 4 introduces the data used for this study and explains the methodological technique applied. Section 5 describes the parks under research and justifies the treatment and control groups as valid counterfactuals. Section 6 follows with the results obtained for each of our variables of interest. Finally, I conclude in Section 7 and Section 8, also discussing the implications and limitations of this study and potential avenues for future research.

2. STATE OF THE ART

2.1. Green gentrification

The term gentrification was first coined by the sociologist Ruth Glass in 1964 in the context of studying urban changes in London and, since then, a lot of empirical research has been conducted aiming to understand better this phenomenon. In the words of Glass (1964, p. 18): *One by one, many of the working-class quarters have been invaded by the middle class – upper and lower… Once this process of "gentrification" starts in a district it goes on rapidly until all or most of the working-class occupiers are displaced and the whole social character of the district is changed.* Gentrification describes the process by which working class residential and degraded neighbourhoods are developed and experience an improvement on the attractiveness of the area which increases its property values, and housing prices, and consequently, trigger a displacement of existing lower income residents who are being replaced by rich, white, and more educated residents (the "gentry").

When the cause of this increase in local property values is a greening practice, we talk about environmental, ecological, or green gentrification; also known as urban green space paradox (Wolch et al., 2014). We understand greening practice as the opening or rehabilitation of public greenspaces as well as other green initiatives such as the development of public transportation, the increased in buildings' energy efficiency, the provision of locally sourced food or the improvement of recycling programs (Gould & Tammy, 2016). This paradox stresses the non-inclusive effects of creating a climate-protective infrastructure: land speculation, large-scale real estate redevelopment, rise in housing prices and the subsequent displacement of socially vulnerable residents living around. The opportunity of appropriation of the exclusive benefits obtained from investing in renaturing projects creates an alliance between municipalities, private investors and privileged residents aiming to exploit these potential "green rents" (Kotsila et al., 2023).

2.2. Literature review

In this section, I provide an examination of the relevant literature and a synthesis of existing research on green gentrification, aiming to identify gaps, key theories and concepts that contribute and contextualize this study.

Regarding the study area of green gentrification case studies, 70% of them have examined at least one US city and only 16% were conducted in non-Anglo-Saxons countries, mostly from Europe[1] (Quinton et al., 2022). Many studies documenting this type of gentrification have been observed in countries like the US (Rigolon & Németh, 2020), Spain (Anguelovski et al., 2018), Belgium (Goossens et al., 2020), and South Korea (Kwon et al., 2017) and more concretely in cities like Atlanta (Immergluck & Balan, 2018), Chicago (McKendry & Janos, 2015), Detroit (Montgomery, 2016; Safransky, 2014), New York (Checker, 2011), Portland (Goodling et al., 2015; Lubitow & Miller, 2013), San Francisco (Marche, 2015), Seattle (Dooling, 2009), Toronto (Dale & Newman, 2009), and Vancouver (Dale & Newman, 2009; Quastel, 2009). Over 55% of these studies followed a qualitative approach using interviews, observations, and the revision of various materials like government documents and articles (Quinton et al., 2022).

Certain attributes of the park may be determinant on the magnitude, or the extent, of the gentrification process observed in the surrounding area. The specific location of a park within a city, the extent of its surface and the functionality of the park (sports-oriented, recreational, natural, or ecological, cultural…) are clear examples of parks' features which may influence gentrification. Rigolon and Németh (2020) tested whether the location, size, and function of new parks in the United States built in the periods 2000-2008 and 2008-2015 are good predictors of gentrifying trends in the nearby census. Their findings show that those parks with an active transportation component (i.e., a greenway park) triggered gentrification compared to other parks, and that those located closer to the downtown tend to foster gentrification more than those located on the city's periphery. They assessed gentrification through the analysis of the following patterns: increases in the median household income, increases in the percentage of people with a bachelor's degree and either a rise in median gross rent or a median housing value greater than that of their city in the same period.

Density of greenspaces in a specific area and the quality of the parks can also play a role in determining the impact of gentrification. From the analysis conducted in different North American cities (Anguelovski et al., 2022), it was found in the city of Philadelphia that bigger and more aesthetic parks produce a greater impact around themselves and that the neighbourhoods more prone to suffer green gentrification are

[1] Barcelona is the European city where most case studies have been done.

those located near to other gentrified neighbourhoods and near to the city centre. In New York City, the number and density of greenspaces in a census tract was positively correlated with gentrification and positively impacting housing prices.

As it has been mentioned in the previous section, the benefits of greening are exclusive to certain privileged citizens, fact that should be associated with a lack of enough attention paid by the responsible of greening projects to the needs and interests of the most vulnerable communities. Previous research suggests that a high level of inequality is associated with a low rate of participation of low-income residents either due to the incompatibility of common goals between different status groups of society or due to a lack of resources to participate in social life (Lancee & Van de Werfhorst, 2012). Community involvement in the design of green practices has been studied by McKendry and Janos (2015) in Seattle and Chicago who argued the crucial role citizens´ participation plays in terms of social equity and community coherence. This paper uses qualitative data such as government documents and reports, newspapers articles, among others, to analyse the local government initiatives and the community efforts in its engagement.

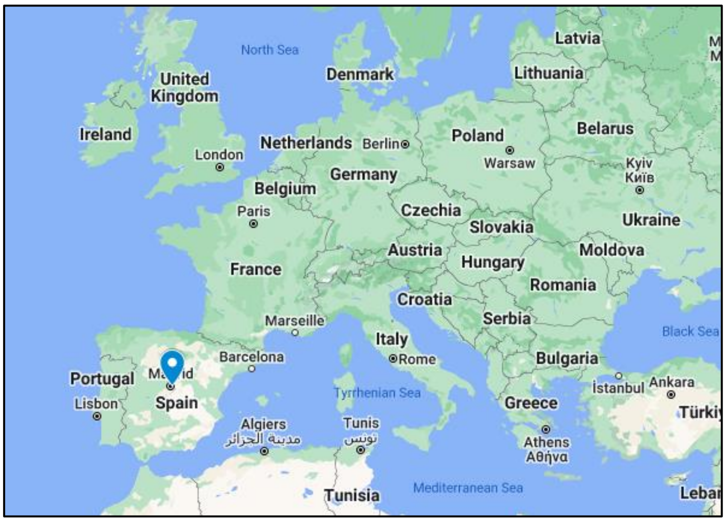
My research primarily finds its inspiration in a particular spatiotemporal analysis in Barcelona (Anguelovski et al., 2018). The study seeks to analyse any possible gentrification trends in the areas surrounding 18 different greenspaces located in socially vulnerable neighbourhoods of Barcelona during the 1990s and early 2000s. As a general quantitative approach, they measured change over time across a set of sociodemographic and economic variables. They gathered data at the census tract level for the following indicators: percent of population with a bachelor's degree or higher; percent of population over 65 years old living alone; household income; home sales values; percent of immigrant population whose nationality is from the Global North; and percent of immigrant population whose nationality is from the Global South. Scholars have argued that collecting data for more than one variable allows for a more accurate reflection of the process of gentrification although which of them truly defines the process is still in debate.

The researchers (2018) conducted an OLS regression which relates the sociodemographic variables with the distance to parks variable assuming spatial stationarity, that is that this relationship is constant across space. They have analysed each indicator in the area around parks using 100m, 300m, and 500m buffers. They concluded that gentrification trends have occurred in those neighbourhoods with a historical industrialization, whereas in *extremely dense distressed* areas it did not happen.

3. WHY MADRID?

My research is focused on Madrid, the capital city of Spain (Figure 1), to examine the process of green gentrification. The geographical scope of this study is justified on several grounds including data availability, an existing literature gap, and especially, the attractiveness of the city of Madrid from an empirical point of view (Orueta & Seoane, 2012; Tomàs et al., 2011).

Figure 1. Madrid, the capital of Spain



Source: Google Maps

At the beginning of the 1940s, just after the end of the Civil War, Madrid, as many other Spanish cities, was totally devastated by fascism and there was an extreme social situation where famine and misery occupied the whole territory. As Orueta and Seoane pointed out (2012), during the 50s, the city was expanded by the annexation of some surrounding municipalities until reaching a total population of 1,724,674 people in 1955. During this decade, Madrid was a focus for immigration from different Spanish regions and the southern city's neighbourhoods were specially characterized by a poor-quality built environment and enormous deficits in basic street infrastructure and public services. This socio-spatial structure remained being polarized through the years, fact that brings to our study an interesting comparison perspective. In the *1963 Plan General de Madrid* the socio-spatial segregation of the city was not by far solved, but the opposite: the west and north-west part of the city was growing extensively with low-density population and thus a better environmental quality; whereas the east and specially the south was intensively growing in residents and was the place for many industrial pollutant activities. Moreover, during the 1960s, there was a *boom* in the construction sector of low-quality housing which led to the occupation of the city's periphery areas, turning Madrid into a disorganized and disconnected urban structure.

During the 70s, Madrid experienced a substantial economic recovery and its population increased to 3,120,941 people. With the first democratic elections in 1979, the urban agenda was reconducted prioritizing the construction of new equipment and the improvement of a collective transport network according to the demand of social claims. Unfortunately, poverty and exclusion rates were still concentrated at the same areas of the city (east and south). During that period, intraurban migration flow was characterized by the movement of low-income families from the city centre to the periphery and by the movement of high-income families towards north and west regions, less populated areas and with higher environmental quality (Orueta & Seoane, 2012).

As a remarkable fact, the community of Madrid had a population growth of 12% between 1993 and 2003, whereas the land opened for development was growing at a 47% rate. Even the high index of housing per individual and the soft demographic growth in Madrid, there was a part of the population whose basic shelter needs were not covered. Resources existed, but they were not available for everyone. Preteceille (2000) stated that Madrid is currently one of the European cities with the highest social economic segregation.

Nowadays, Madrid has an extensive green infrastructure which encompasses big forest parks, historical parks, urban parks, green walls, and landscaped roofs in some buildings, both from municipal and private management. Forest parks occupy 42% of the green surface of the city and urban parks or gardens, which are more available to citizens in terms of geographical proximity, represent a 34%. The vast majority of the parks were created for a landscape use (96.3%), leaving behind those oriented towards sportive, educational, and cultural uses (Ayuntamiento de Madrid, 2018).

In 2017, the City Council of Madrid was managing a total of 5,800 ha. of green areas, representing 9.6% of the city's total surface. It is worth to mention that the green surface per inhabitant (m^2/inhabitant) in Madrid is 18.26, which significantly exceeds the optimal value of 10 for urban environments. However, this value oscillates depending on the district we are referring to. Another oscillating value is the 0.47 trees per inhabitant, which increases to 6.11 in the district of Moncloa-Aravaca but falls to 0.02 in Chamberí. The city also benefits from a rich tree diversity, with 480 different identified species, among which stands out the pinyon pine (*Pinus pinea*).

Some other important insights are that 93.57% of the population under 9 years old in Madrid has children's areas available in their proximity. 84.12% of the citizens live within a distance of less than 200 meters from a park larger than 1,000 m^2 (below the optimal level) and 99.7% of the population reside within a distance of less than 2 kilometres from a park larger than 10,000 m^2 (Ayuntamiento de Madrid, 2018).

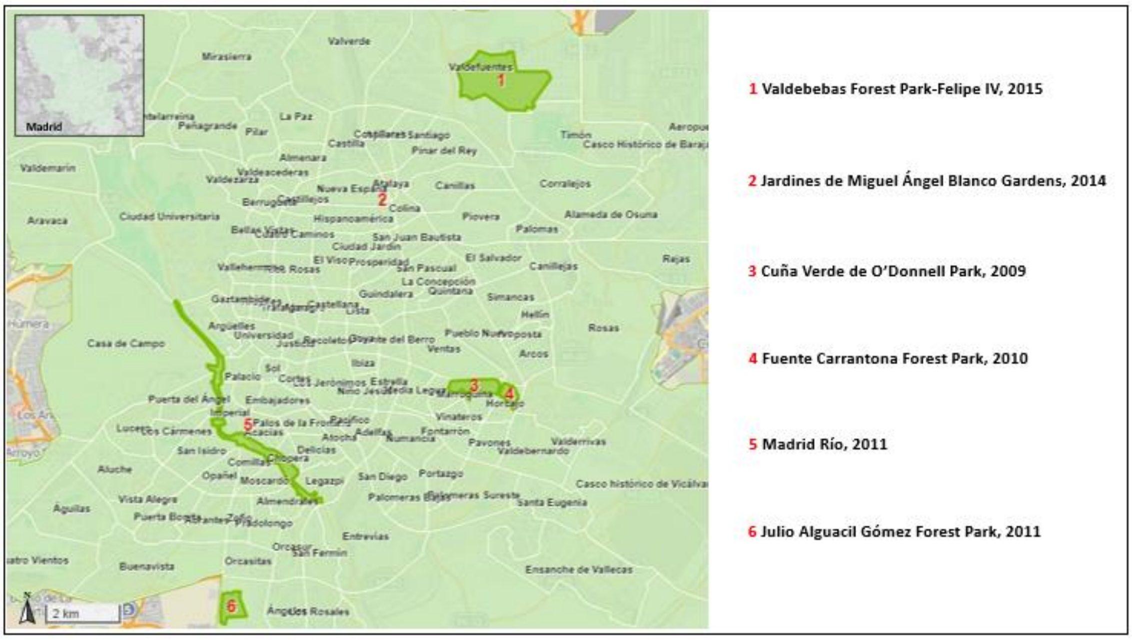
Because of all stated above, the city of Madrid is a geographical area whose socioeconomic and spatial conditions give me an interesting setting to analyse green gentrification trends. The availability of open data on several variables has also contributed to the selection of the city, much more homogenous and richer than in other cities. On top of that, I have found in the literature review, on my knowledge, a gap concerning Madrid's green gentrification and I want to contribute to it with this research.

4. DATA AND METHODOLOGY

4.1. Data

For this study, I have selected those parks which were opened to public from 2009 to 2015 (Figure 2). The starting year was determined according to the year from which data for my variables of interest was publicly available and the ending year was chosen in order to be able to analyse the impact of the park three and six years after its inauguration. This selection has been conducted thanks to the information obtained from the urban green spaces catalogue provided by the City Council of Madrid (Medio Ambiente y Movilidad, 2021).

Figure 2. In green, parks built between the period 2009-2015 within the city of Madrid



Source: own elaboration with Instamaps

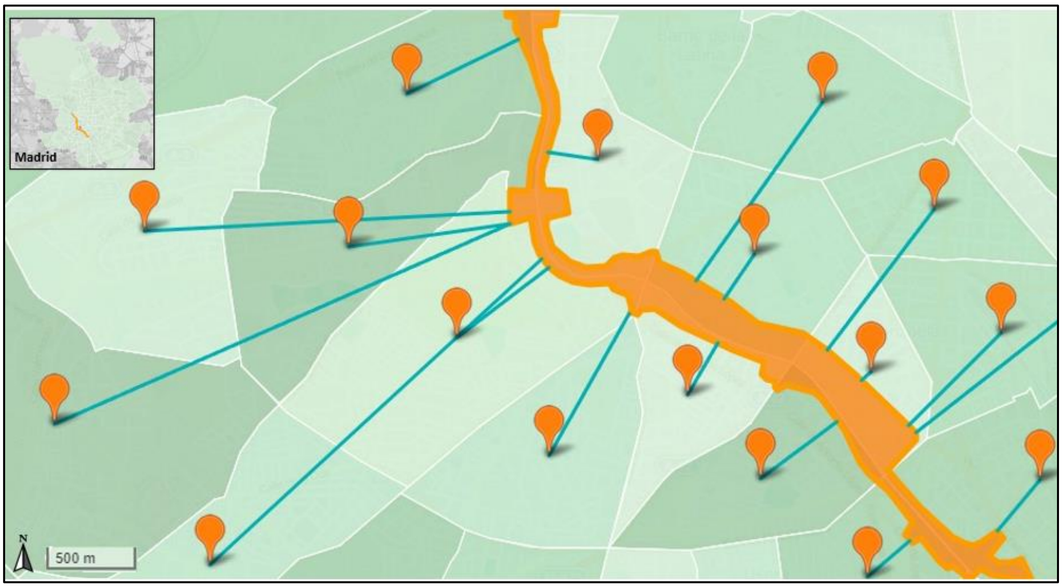
The spatial coverage of the study considers the following neighbourhoods: Puerta del Ángel, Los Cármenes, San Isidro, Opañel, Comillas, Moscardó, Almendrales, Legazpi, Delicias, Chopera, Acacias, Imperial, Palacio, Argüelles, Nueva España, Hispanoamérica, Atalaya, Colina, Valdefuentes, Orcasitas, Marroquina, Horcajo, Media Legua, Vinatero, and Ventas. These neighbourhoods contain six (forest) parks and gardens inaugurated between the period 2009 and 2015.

Once the parks were selected, I had to gather data at the minimum possible unit of analysis from the different sociodemographic and economic indicators normally used in other green gentrification studies. The main source of data is the open data from The City Council of Madrid (*Ayuntamiento de Madrid | Banco de Datos de Madrid*; *Panel de indicadores de distritos y barrios de Madrid. Estudio sociodemográfico - Portal de datos abiertos del Ayuntamiento de Madrid*) and from the *Instituto Nacional de Estadística* (INE). I found some variables available at the census tract level, but the neighbourhood level was the minimum at which data for the whole set of variables of interest was publicly accessible. I collected data on the percentage of the population older than 65 years old; the percentage of the population over 65 years old living alone; the percentage of the population with foreign nationality; the unemployment rate; the percentage of the population with high level education[2]; annual net household incomes; and second-hand housing prices (€/m^2). The selection of the gentrification indicators used in this study was based on the criteria followed in the research done in the city of Barcelona (Anguelovski et al., 2018). These are key variables that reflect gentrifying trends. I collected data for the year of the inauguration of each of the parks (*t=0*), for three years after *t=0* (*t=1*), and for six years after *t=0* (*t=2*) aiming to study the short-term and the medium-term impact. I calculate the change of the chosen variables from period *t=0* to *t=1* and from *t=0* to *t=2*, which will be our dependent variables. The change in all the variables is measured with percentage points (pp.) except for the change in the annual net household income and the second-hand housing prices, which are measured with percentages (%). Prices and incomes have been adjusted for inflation, working with real variables with 2021 as the base year. I have used the general CPI to calculate real incomes and the housing CPI to calculate real housing prices.

The independent variable is the distance (in meters) from each neighbourhood's centroid to the closest park's boundary (see an example in Figure 3).

[2] i.e. holding a bachelor's degree, higher studies, architect or engineer, non-university higher studies, PhD, and postgraduate studies.

Figure 3. Computing the distance from each neighbourhood's centroid to the closest park's boundary. Example in Madrid Río (area in orange)



Source: own elaboration with Instamaps

Table 1 summarizes the descriptive statistics of the independent and dependent variables in my analysis.

Table 1. Descriptive Statistics

Variable	Observations	Mean	SD	Min	Max
DISTANCE TO PARKS	47	1124.3	747.7	0	2980
$\mathrm{alone65}_3$	47	0.7	2.1	-0.7	14.6
$\mathrm{alone65}_6$	47	1	2.2	-0.4	15.5
$FOREIGN_3$	47	-3.1	2.3	-6.8	0.9
$FOREIGN_6$	47	-3.4	3.1	-8.6	2.5
$UNEMPLOYMENT_3$	47	1.6	1.8	-2.6	4.8
$UNEMPLOYMENT_6$	47	-0.6	1	-3.2	1.5
$HEDUC_3$	47	3.4	1.9	-3.4	7.8
$HEDUC_6$	47	6.1	2.9	-1.7	11.1
$RINCOME_3$	47	5.5	3.3	-2.8	14.7
$RINCOME_6$	47	20.4	6.9	4.5	38.9
$RPRICE_3$	43	-13	18	-34.5	35
$RPRICE_6$	42	5.1	19.4	-22.6	49.4

Note: This table displays descriptive statistics for each variable. The statistics estimated are the number of observations, the mean, the standard deviation, the minimum and the maximum. The subindex represents the number of years after the inauguration of the park.

Source: own elaboration with data from Madrid City Council and Instamaps

I have also introduced in my model some covariates to smooth the prediction of the variables of interest. I define below each of the remaining terms that appear in the regressions:

Table 2. Description of the regression terms

VARIABLE	DEFINITION
dcutoff	Distance from each centroid's control neighbourhood to the cut-off (meters)
treatment	Takes value 1 for units in the treatment group and 0 for those in the control group
d2011	Takes value 1 for those parks inaugurated in 2011 and value 0 for those inaugurated in any other year
baseline	Baseline value (at t=0) of the dependent variable of each regression to control for the starting point of each neighbourhood. I have worked with logarithms for income and price variables
income_mean	Takes value 1 for those neighbourhoods whose mean is above the city's income mean at t=0 and 0 for those below
MA	Takes value 1 for those neighbourhoods corresponding to Miguel Ángel Blanco Gardens
FV	Takes value 1 for those neighbourhoods corresponding to Felipe IV Forest Park
JA	Takes value 1 for those neighbourhoods corresponding to Julio Alguacil Gómez Forest Park
DC	Takes value 1 for those neighbourhoods corresponding to Julio Alguacil Gómez Forest Park
$\boldsymbol{POP_3}$	Change (%) of population in each neighbourhood from t=0 to t=3
$\boldsymbol{POP_6}$	Change (%) of population in each neighbourhood from t=0 to t=6
treatment:income_mean	Interaction term to know how treatment effect and being above/below Madrid's income mean relate between each other
dcutoff:treatment	Explains the effect of the distance to park in the treatment group once you have added the coefficient of the *dcutoff* variable to this one

Source: own elaboration

4.2. Methodology. A Geographic Regression Discontinuity Design (GRD)

In this paper, I analyse if the creation of new green urban amenities has a causal effect on potential gentrification trends in the neighbourhoods around them using a natural experiment based on geography. The interpretation of the green urban parks as a natural experiment relies on the assumption that the establishment of these green amenities in the specific places they are located, rather than in another place, occurred for reasons unrelated to pre-existing differences in the environment or in the population that could affect our outcomes of interest (Lowes et al., 2017).

The design implemented is a sharp regression discontinuity (Huntington-Klein, 2021). This design has recently become one of the most quasi-experimental strategies used in empirical research looking for causal effects (Calonico et al., 2014). The idea is to assign a binary treatment, *T*, as a function of a covariate, in this case distance, in a way that the assignment to treatment will be a deterministic function of the running variable (distance). I also have to define a cut-off, that is the value of the running value that determines which of the units of analysis (neighbourhoods) will be part of the treatment (*T=1*) or control group (*T=0*). If you are on one side of the cut-off value, you are treated but if you are on the other side, you are not. The bandwidth will limit the geographic scope of the analysis, showing the boundary limit of the control group. The main point and what gives the name to this design is that the probability of receiving the treatment jumps discontinuously at the cut-off whereas all other potential confounders vary smoothly (Keele et al., 2015). Assuming that S_i is the score (given by two coordinates) that determines the treatment assignment (*T(s)=1* for those points inside the set of locations that receive the treatment and *T(s)=0* for those that do not), *β* is the set that collects the locations of all boundary points, and *b* denotes a single point on the cut-off (or boundary), I can formulate the following identification assumption:

Assumption 1. The conditional regression functions are continuous in *s* at all points *b* on the boundary:

$$\lim_{s \to b} E\{Y_{i0} / S_i = s\} = E\{Y_{i0} / S_i = b\}$$
$$\lim_{s \to b} E\{Y_{i1} / S_i = s\} = E\{Y_{i1} / S_i = b\}$$

for all $b \in$ *β.*

The design assumes that I have assigned the status of treatment to areas that only differ from the control areas by the fact of receiving the treatment -being at a certain distance from the parks-.

Assumption 2. (Conditional geographic treatment ignorability). The potential outcomes are independent of treatment assignment conditional on observed covariates (Keele et al., 2015).

Theoretically, it is not necessary to adjust for baseline covariates because the treatment assignment via geographic location creates as-if random variation in treatment assignment, thus it is considered as good as randomly assigned -as in randomized controlled trials-. Since assignment to treatment is the only thing that changes abruptly at the threshold, we can attribute the change of the outcome variable to the effects of the treatment. In order to consider this framework as a local randomized experiment, I must assume that individuals are unable to self-select the distance at which they are located from the cut-off to not undermine the validity of the design and make potential outcomes discontinuous (Lee, 2008).

A common limitation of this design is a small sample size because the observations which are far away from the threshold are excluded from the analysis due to its little importance. In this study, little data availability is added to this limitation: my unit of analysis is neighbourhoods, not households or individuals. However, I think that widening our bandwidth would bring lack of precision to the study since estimation results use to be highly sensitive to its choice. It exists a trade-off between noise and bias: if we narrow the bandwidth, the number of observations will decrease, so the estimate of the treatment effect becomes noisier, but bias should not concern us that much.

In GRD designs, we often face compound treatments or multiple treatments that affect the outcome of interest simultaneously. This normally occurs because the cut-off can coincide with the boundary of some administrative units and thus, it may exist another treatment that is beyond our interest. So, the treatment effect can vary according to the specific location, leading to spatially located effects. On the following section, I provide some evidence about the differences within the districts under this study between certain indicators. Fortunately, I will see how the matched comparisons are good counterfactuals.

Following the study by Card and Krueger (1993) which estimated the effect of increasing the minimum wage on employment by comparing fast-food restaurants in New Jersey to restaurants in eastern Pennsylvania -adjacent areas-, here I compare neighbourhoods near the park with its adjacent neighbourhoods. Since I only have data available at the neighbourhood level, I will take as a reference point for each of the neighbourhoods its centroid in a way that data compiled for each specific neighbourhood will be referenced to its centroid. The next step is to choose the boundary that will delimit my treatment group. What would make sense is to analyse the data at three distances of relative proximity to parks (i.e., 100 meters, 300 meters, and 500 meters) (Anguelovski et al., 2018), but in this analysis, it is impossible to replicate this framework since I cannot disentangle data in the same neighbourhood. For this reason, I am going to work with a wider buffer.

It is important in this point of the explanation to highlight the importance of a specific area of the study and hence its determinant role in the identification of our buffer (cut-off). We must pay attention to the neighbourhoods at the south of Madrid Río (below the orange area in Figure 4) because, given its longest shape than those at the north, I must consider a buffer which prioritizes including its centroids since, if I just prioritize those at the north, the buffer would be too small to include those at the south. Moreover, these neighbourhoods are particularly interesting to examine due to its higher vulnerability than those surrounding the other parks under the study. Having said that, we can see in Figure 4 that if we take a buffer of, for example, 1000 meters, the neighbourhoods at the south of Madrid Río are included. Even if the buffer's radius is too big compared to what is normally used[3], I clarify that it is a requirement to consider the nearest neighbourhoods to the park.

Once the areas belonging to *T=1* condition are defined, I must choose the control group. I propose a pair matching framework where the total sum of geographic distances between matched pairs is minimized. The neighbourhood near the selected buffer (adjacent) is a valid counterfactual for the treated group because placement in one of the two areas can be seen as random very near the boundary (Keele et al., 2015). It is true that in my study, this assumption is easily violated because I cannot compare data just at the boundary; however, I proceed anyway having this in mind and considering the level of inequality in each district when interpreting the results. Therefore, the bandwidth of the study ends when the centroid of the adjacent neighbourhood to each treated area is included. It does not make sense to consider another buffer to limit the bandwidth because I am only concerned about the adjacent areas: a wider buffer would introduce neighbourhoods in the analysis even if they are not adjacent (due to the heterogenous shape of these areas) and the assumption 1 would be violated. I match without replacement, which requires each treated and control subject to be matched at most once.

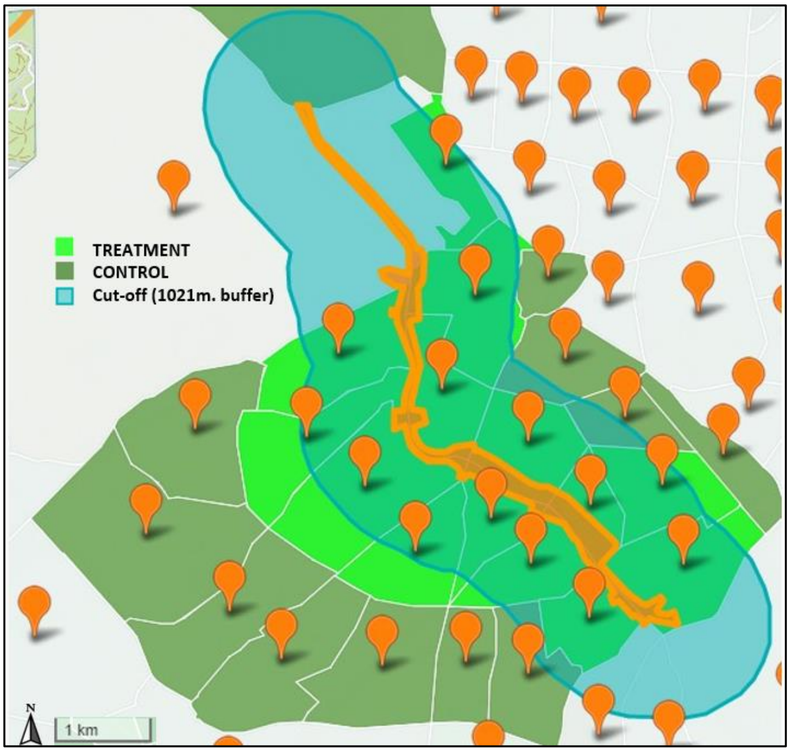
Each treatment neighbourhood is matched to its adjacent one prioritizing matches between pairs which belong to the same district aiming to minimize any potential confounders between the comparison groups. The treatment group is composed by 25 units whereas the control group has 22 units. The difference in the shape of the neighbourhoods forced me, in some cases, to compare two units in the treatment group with just one unit in the control group. I preferred to follow this method instead of adding another unit in the control group to achieve the same number of observations in both groups even if it was not a good counterfactual due to its further location from its matched paired.

The last step to finish with the identification of the treatment and control group is to be more specific in the representation of my cut-off. Due to data availability, I do not care about the space between the furthest centroid from the park in the treatment group (*1*) and the closest centroid to the park in the control group (*2*). Hence, the cut-off of this analysis will be the buffer located at a distance from the park equal to the mean of the distances of point *1* and point *2*. Following this procedure, I ensure that the cut-off is established in a way that all treatment centroids are located on one side and all control units on the other.

[3] 400m Euclidean distance buffer as an easily walkable estimate of a standard catchment for a greenspace (Anguelovski et al., 2022).

In this study, distances are calculated through a line that links each centroid with the closest park's boundary thanks to *Instamaps* and *Mymaps,* where I have also created the polygon which correspond to each park. The longest distance from the treatment neighbourhoods' centroid to the park is 982 meters and the shortest distance from the control neighbourhoods' centroid to the park is 1,060 meters; so, the cut-off is set at the 1,021 meters buffer that surrounds each of the studied parks (see in Figure 4).

Figure 4. The establishment of the cut-off (1,021m.) that assigns neighbourhoods to treatment or control group. The example of Madrid Río.



Source: own elaboration with Instamaps

Let's introduce the regression discontinuity with OLS that I use to predict the outcome (Huntington-Klein, 2021):

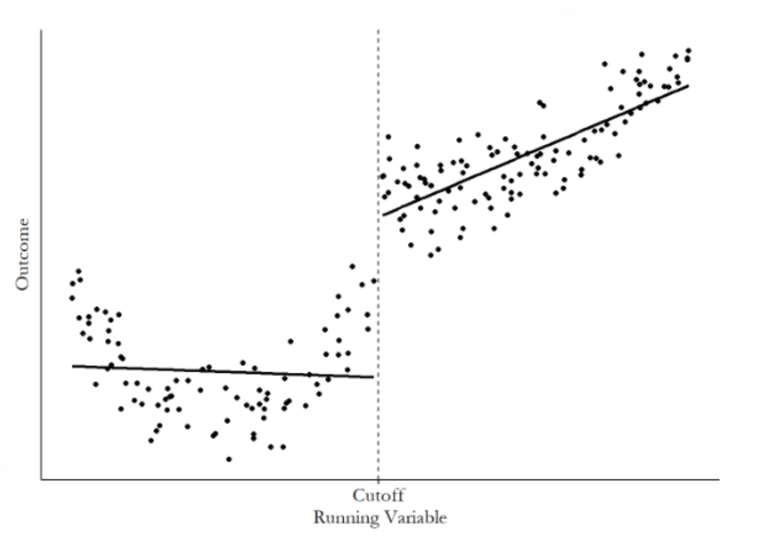
$$Y = \beta_0 + \beta_1(Running_i - Cutoff) + \beta_2 Treated_i + \beta_3(Running_i - Cutoff)\, x\, Treated_i + \varepsilon_i \qquad (1)$$

The running variable is the distance from the centroid of each neighbourhood (both treatment and control) to the nearest boundary of the park. *Running – Cutoff*[4] takes a negative value for the treatment group and a positive value for the control group, where cut-off equals 1,021 meters.

[4] *Running – cutoff* is defined as *dcutoff* in my regression.

From regression (1), I obtain one straight line (Figure 5) with the intercept β_0 and the slope β_1 (control) and another one with the intercept $\beta_0 + \beta_2$ and the slope $\beta_1 + \beta_3$ (treatment). Assigning the 0 value to my running value at the cut-off permits me to understand each of these intercepts as the prediction at the cut-off. Therefore, β_2 corresponds to the estimate of the regression discontinuity effect or the change in intercepts from line to line at the threshold (Huntington-Klein, 2021).

Figure 5. Regression Discontinuity Estimated with Linear Regression with an Interaction



Source: Huntington-Klein, 2021, fig. 20.5

Even if I have mentioned before that this design does not have to include any control variables because it assumes that the assignment to treatment and control group is almost random, I think that I should control for the effects of unobserved variables that might influence the dependent variable in my model because it is not as good as the theoretical one in terms of the assumptions with which it should be consistent. For that reason, I include the following additional terms: variables controlling for the park which the observations refer to, capturing any differences between parks; variables controlling for the year when the park was inaugurated; a variable that takes a value of 1 if the annual household income mean is above the income city mean and 0 it is below it (*income_mean*); and finally, I also introduce a baseline of each outcome variable for taking into account the starting point level of each observation. I also introduce an interaction term between the *treatment* variable and the *income_mean* variable because I expect that the treatment effect will be more significant in poorer neighbourhoods.

5. CASE STUDIES

This section aims to describe the six different green parks selected to be the subject of this study. I have gathered descriptive information (Medio Ambiente y Movilidad, 2021) regarding the characteristics of each park, and I also include the treatment and control neighbourhoods corresponding to each park, according to the methodology explained above. The criteria for this selection have entirely been data availability which have restricted the period in which the parks chosen had had to be inaugurated. At the end of this section, I also justify in terms of district inequalities why the control group works as a counterfactual beyond the fact that each control neighbourhood is adjacent to a treatment neighbourhood.

5.1. Madrid Río

Inauguration date: 2011

Total surface: 1,210,881m^2

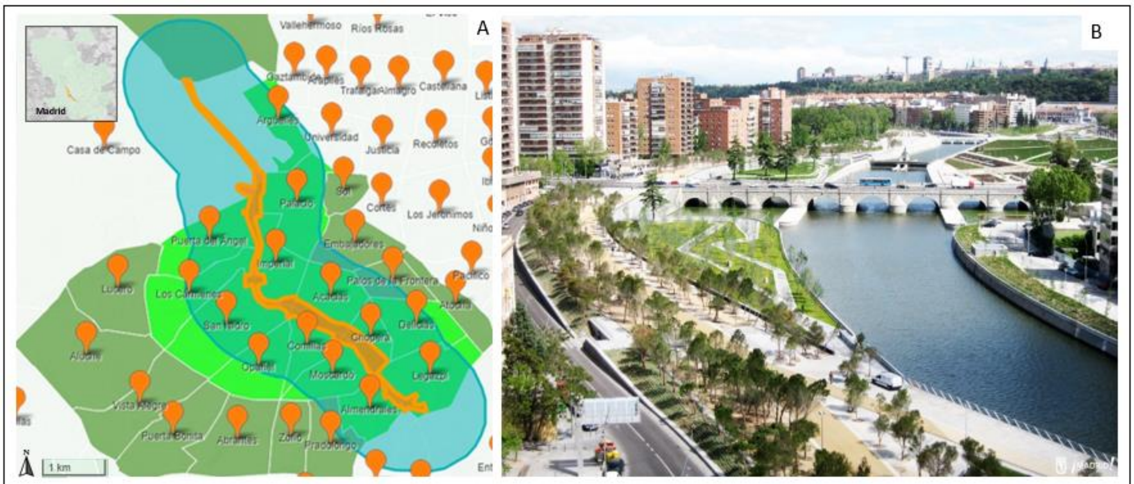
Treatment neighbourhoods: Puerta del Ángel (Latina), Los Cármenes (Latina), San Isidro (Carabanchel), Opañel (Carabanchel), Comillas (Carabanchel), Moscardó (Usera), Almendrales (Usera), Legazpi (Arganzuela), Delicias (Arganzuela), Chopera (Arganzuela), Acacias (Arganzuela), Imperial (Arganzuela), Palacio (Centro), and Argüelles (Moncloa).

Control neighbourhoods: Lucero (Latina), Aluche (Latina), Vista Alegre (Carabanchel), Puerta Bonita (Carabanchel), Abrantes (Carabanchel), Zofío (Usera), Pradolongo (Usera), Atocha (Arganzuela), Palos de la Frontera (Arganzuela), Embajadores (Centro), Sol (Centro) and Ciudad Universitaria (Moncloa).

Description: The creation of the Madrid Río Park (Figure 6) has been the culmination of a series of interventions that started some years before and that has brought back the ecological equilibrium to the city. In 2005, the Madrid City Council fostered the initiation of a project aiming to rehabilitate the area that had been occupied until that date by the west of the M-30 bypass road (Gobierno de España, 2017). The objective was to transform the Manzanares riverside by its integration into the urban structure and to restore the space that had been freed from traffic. The urban development plan was led by the architect Ginés Garrido and the Burgos and Garrido architecture studios (Burgos&Garrido Arquitectos); Porras and La Casta; Rubio and Alvarez Sala; and by the Dutch landscaping studio West 8. The creation of the park started in 2007 once the M-30 was already dig and it allowed the connection between the neighbourhoods located along both sides of the river through the existence of 33 crossings, unifying the north with the south of Madrid. A project with strong ecological values that seeks to recover forests in the vicinity of the city through a linear and continuous system of green spaces guided through the Manzanares river.

Utilities and services: historic and new pathways that connect both sides of the river, sports facilities (18), children's areas (20), garden, viewpoints (2), terraces to have a drink, nearby hotels, urban beach, canine areas (2), ecological path (8km.), cycling lanes (16.5km.), public toilets (16), banks (318), litter bins (506) and drinking fountains (36).

Figure 6. Madrid Río



A) Treatment (light green) and control (dark green) neighbourhoods
B) Madrid Río Park

Source: A) Own elaboration with Instamaps, B) Madrid City Council

5.2. Miguel Ángel Blanco Gardens

Inauguration date: 2014

Total surface: 3,000m^2

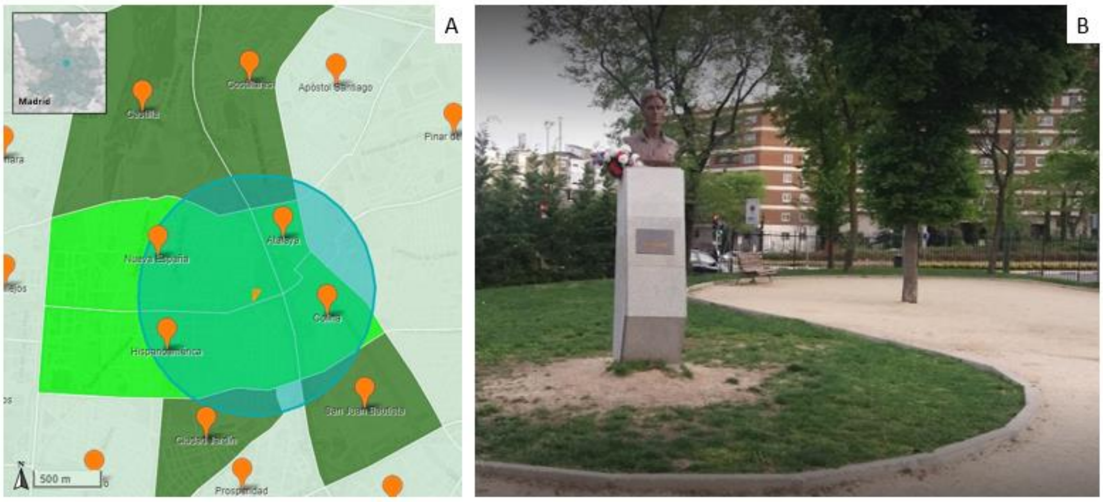
Treatment neighbourhoods: Nueva España (Chamartín), Hispano América (Chamartín), Atalaya (Ciudad Lineal), and Colina (Ciudad Lineal).

Control neighbourhoods: Castilla (Chamartín), Ciudad Jardín (Chamartín), Costillares (Ciudad Lineal) and San Juan Bautista (Ciudad Lineal).

Description: the name of this green area pays homage to Miguel Ángel Blanco, a councillor who was assassinated by ETA in 1997 and whose bust can be found in this green space (Figure 7).

Utilities and services: a children area and a terrace to have a drink.

Figure 7. Miguel Ángel Blanco Gardens



A) Treatment (light green) and control (dark green) neighbourhoods
B) Miguel Ángel Blanco Gardens

Source: A) Own elaboration with Instamaps, B) GoogleMaps, 2018

5.3. Valdebebas Forest Park- Felipe IV

Inauguration date: 2015

Total surface: 2,457,418m^2

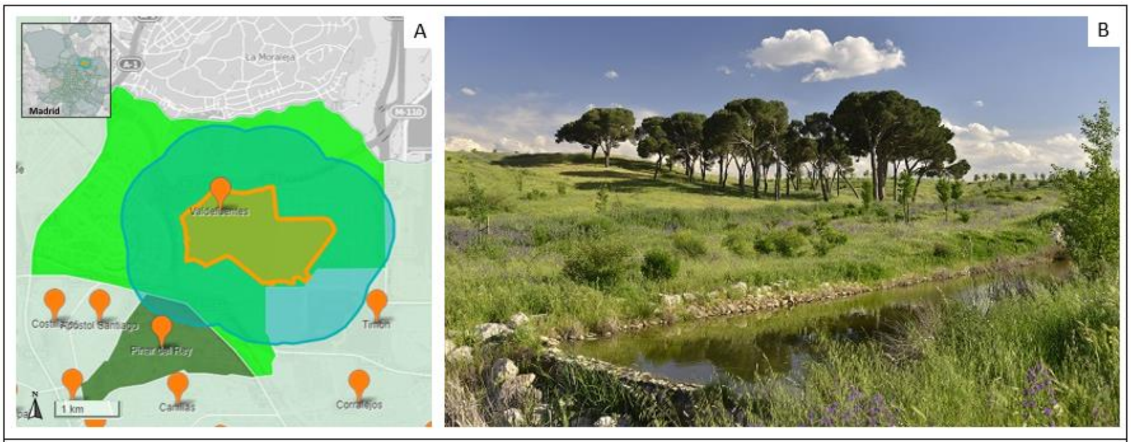
Treatment neighbourhoods: Valdefuentes (Hortaleza)

Control neighbourhoods: Pinar del Rey (Hortaleza)

Description: young forest of native vegetation dominated by stones pines extended over former cultivation areas. The park has several streams and two small lakes. It is primarily a forest park although it has some urban garden areas. Aiming to recreate a forest park within an urban environment, Felipe IV Park represents the different ecosystems found in the centre of the Iberian Peninsula through the combination of each typical vegetation (Figure 8).

Utilities and services: sports facilities (1), children's areas (9), viewpoints (3), canine areas (2), ecological path (1), cycling lanes (7.4km.), public toilets (2), banks (379), litter bins (166), drinking fountains (27), picnic areas, and a round wooden structure, the Labyrinth, that serves as a lookout.

Figure 8. Valdebebas Forest Park - Felipe IV



A) Treatment (light green) and control (dark green) neighbourhoods
B) Valdebebas Forest Park – Felipe IV

Source: A) Own elaboration with Instamaps, B) Madrid City Council

5.4. Julio Alguacil Gómez Forest Park

Inauguration date: 2011

Total surface: 445,878.89m^2

Treatment neighbourhoods: Orcasitas (Usera)

Control neighbourhoods: Orcasur (Usera)

Description: created as an innovative strategy of urban regeneration which integrates social, economic, and environmental aspects aiming to contribute into the sustainable development of Villaverde district. Implementation of an irrigation system which uses regenerated water. Set of tree lines that work as an acoustic screen for the nearby road traffic (Figure 9).

Utilities and services: children's areas (3), cycling lanes (2.7km.), banks (86), litter bins (119), drinking fountains (19).

Figure 9. Julio Alguacil Gómez Forest Park

A) Treatment (light green) and control (dark green) neighbourhoods
B) Julio Alguacil Gómez Forest Park

Source: A) Own elaboration with Instamaps, B) Madrid City Council

5.5. Cuña Verde de O'Donnell Park

Inauguration date: 2009

Total surface: 413,588m^2

Treatment neighbourhoods: Marroquina (Moratalaz), Media Legua (Moratalaz), Vinateros (Moratalaz), Ventas (Ciudad Lineal).

Control neighbourhoods: Estrella (Retiro), Fontarrón (Moratalaz) and Pueblo Nuevo (Ciudad Lineal).

Description: system of green spaces within a forest area which connects urban parks with non-urbanized areas (Figure 10).

Utilities and services: children's areas (3), cycling lanes (2.7km.), banks (86), litter bins (119), drinking fountains (19), a small auditorium, a viewpoint.

5.6. Fuente Carrantona Forest Park

Inauguration date: 2010

Total surface: 225,700m^2

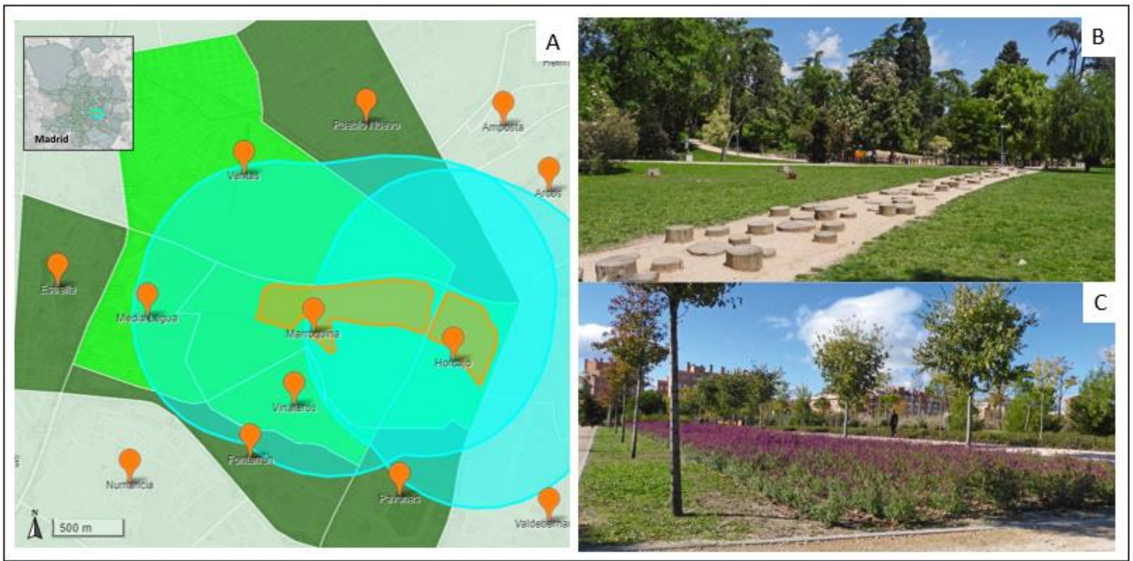
Treatment neighbourhoods: Horcajo (Moratalaz)

Control neighbourhoods: Pavones (Moratalaz)

Description: The park was created thanks to the trees that were transplanted from different parts of the city in where large infrastructure works were carried out in prior years (Figure 10). Established in an old, degraded area, the inauguration of the park meant a significant environmental improvement for the district of Moratalaz.

Utilities and services: children's areas (2), canine area, sport facility, cycling lanes (5.8km.), banks (60), litter bins (29), drinking fountains (3).

Figure 10. Cuña Verde de O'Donnell Park and Fuente Carrantona Forest Park



A) Treatment (light green) and control (dark green) neighbourhoods
B) Cuña Verde de O'Donnell Park
C) Fuente Carrantona Forest Park

Note: These two parks are represented together in the map because they have been treated as one unit due to its geographical and temporal proximity and their shareability of treatment and control neighbourhoods.
Source: A) Own elaboration with Instamaps, B, C) Madrid City Council

I also want to provide an intuition about how disequilibrated the selected districts in my analysis are to give another reason why they are valid for a causal analysis. The City Council of Madrid published in 2007 an analysis called *La Evolución de los Equilibrios-Desequilibrios intraurbanos en la ciudad de Madrid* (City Council of Madrid, 2007) which offers an index for each of Madrid's districts for the period 1991-2000 and 2001-2006 that represents the level of divergence within each area considering several indicators such as the percentage of young people, the percentage of university students, the percentage of unemployed, the number of persons living in each household, the mean atmospheric SO_2, among others. Index values oscillate above and below 1, which is the reference point, and the more they differ from 1, either positively or negatively, the bigger is the disequilibrium in a certain district regarding the indicators mentioned above. Table 3 classifies Madrid districts in three different groups according to their level of equilibrium during the period 2001-2006.

Table 3. Level of equilibrim-disequilibrium across Madrid districts

Slight disequilibrium	Moderate disequilibrium	High equilibrium
Chamberí	San Blas	Arganzuela
Centro	Retiro	Ciudad Lineal
Salamanca	Villa de Vallecas	Fuencarral- El Pardo
Chamartín	Hortaleza	Moncloa-Aravaca
	Carabanchel	Barajas
	Puente de Vallecas	
	Usera	
	Villaverde	
	Vicálvaro	
	Latina	
	Tetuán	
	Moratalaz	

Source: *La Evolución de los Equilibrios-Desequilibrios intraurbanos en la ciudad de Madrid,* 2007

Focusing on the districts of my analysis, we see that almost 32% of the units are in those neighbourhoods with a high level of equilibrium, 53.2% of them have a medium level of equilibrium, and just 14.9% of them suffer from higher levels of disequilibrium, although not that extremes as they were in the previous period (1991-2000).

All in all, because of the assumption that adjacent neighbourhoods are good counterfactuals given their proximity, because I have prioritized the matching of neighbourhoods which belong to the same district, and because of the contribution of the previous equilibrium-disequilibrium analysis to this research, I have been able to conduct the OLS regressions looking for causal relationships and to draw conclusions from them.

6. RESULTS

In this section, I present the results of the analysis across seven indicators of possible gentrification trends (see all the regression results in Table 17, in the appendix). I analyse each indicator for the two periods under study: three years and six years after the opening of the park -starting point of the study period-. Therefore, Madrid Río is studied in 2011, 2014 and 2017; Miguel Ángel Blanco Gardens in 2014, 2017 and 2020; the Valdebebas Forest Park in 2015, 2018 and 2021; Julio Alguacil Gómez Forest Park in 2011, 2014 and 2017; and finally, Cuña Verde de O'Donnell Park and Fuente Carrantona Forest Park, which were condensed together and treated as the same observation due to its geographical and temporal proximity, in 2011, 2014 and 2017. I used data that coincides with the previous list of years or the closest year for which data was available[5]. I use robust standard errors because these are less sensitive to outliers and heteroskedasticity in our data.

6.1. Percentage of population older than 65

Regarding the first indicator, we expect to see a decrease in the percentage of population older than 65 years old in the areas surrounding the newly created green amenities. Older people are often seen as potential victims of displacement, gradually replaced by younger and higher-educated individuals (Hochstenbach and Boterman, 2018).

Table 13 (in the Appendix) shows the average change of the percentage of population older than 65 experienced in the neighbourhoods corresponding to each park (both for treatment and control group, three and six years after parks' inauguration). Almost all values are positive, meaning that there has been an increase in the % of population older than 65. In all the cases except one, the change has been bigger for the control group. Additionally, the OLS model does not find any statistically significant treatment effect, so I am going to focus on the next variable, which higher represents gentrification processes, and it is highly correlated with this one.

6.2. Percentage of population over 65 years old living alone

This indicator is more accurate to analyse potential gentrification trends since elderly people that live alone are more likely to move because of rising costs and changing demographics in their area (Anguelovski et al., 2018). In the appendix, Table 14 illustrates the percentage change of this variable across parks and years.

If we look at the estimates of the model (Table 4), we see that the treatment effect is not significant. It is still interesting to remark that the F-statistic is statistically significant at a 0.01 level because some of the fixed effects of the model are relevant, especially those controlling for the Felipe IV Park and for the change in total population from time 0 to 3 and 6 years after. This last one is negative meaning that an increase in the total population decreases the change in % of population living alone, suggesting that it may be that any change in the proportion is due to change in the population rather than in the actual number of elderly people living alone. Another important remark is that my model explains 96.6% (3 years after) and 93.8% (6 years after) of the variance in the percentage of the population over 65 living alone.

[5] The income at t=0 of parks inaugurated in 2011 corresponds to the year 2013. I count three and six years from 2013. Data before 2011 was not available for all the indicators.

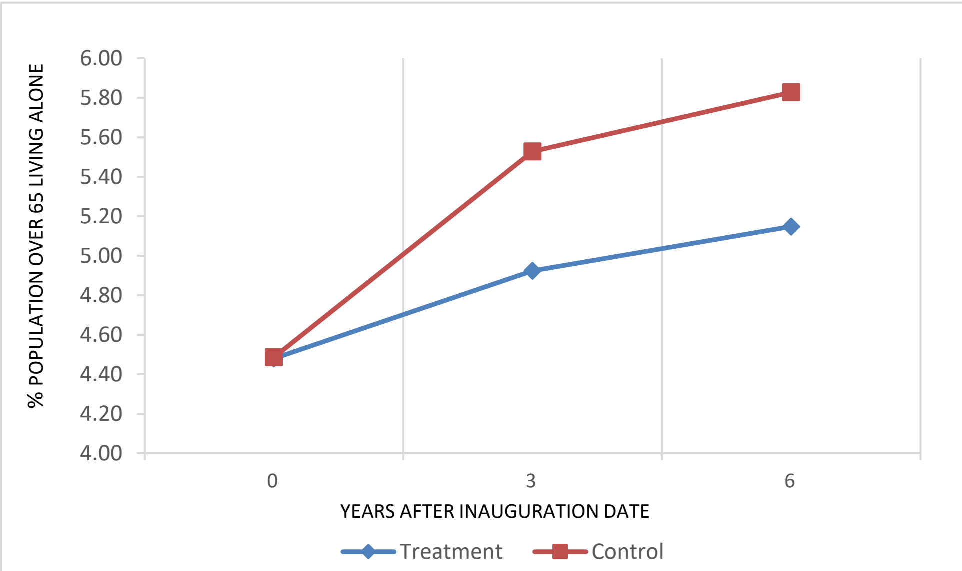
Table 4. Regression estimates for percentage change of population older than 65

	$alone\_65_3$	$alone\_65_6$
Treatment	0.307 (0.221)	0.405 (0.319)
baseline	-0.101* (0.058)	-0.154* (0.086)
income_mean	0.444* (0.237)	0.731** (0.343)
FV	3.213*** (0.357)	5.552*** (0.458)
POP	-0.160*** (0.007)	-0.137*** (0.008)
Constant	0.156 (0.297)	0.454 (0.427)
Adjusted R^2	0.966	0.938
F-statistic	121.105*** (df = 11; 35)	63.784*** (df = 11; 35)

Note: *p<0.1; **p<0.05; ***p<0.01
Source: own elaboration with data from Madrid City Council

Figure 11 shows the increase in the variable of interest over time and a similar evolution both in treatment and control groups.

Figure 11. Evolution of % of population over 65 living alone



Source: own elaboration with data from Madrid City Council

6.3. Percentage of population with foreign nationality

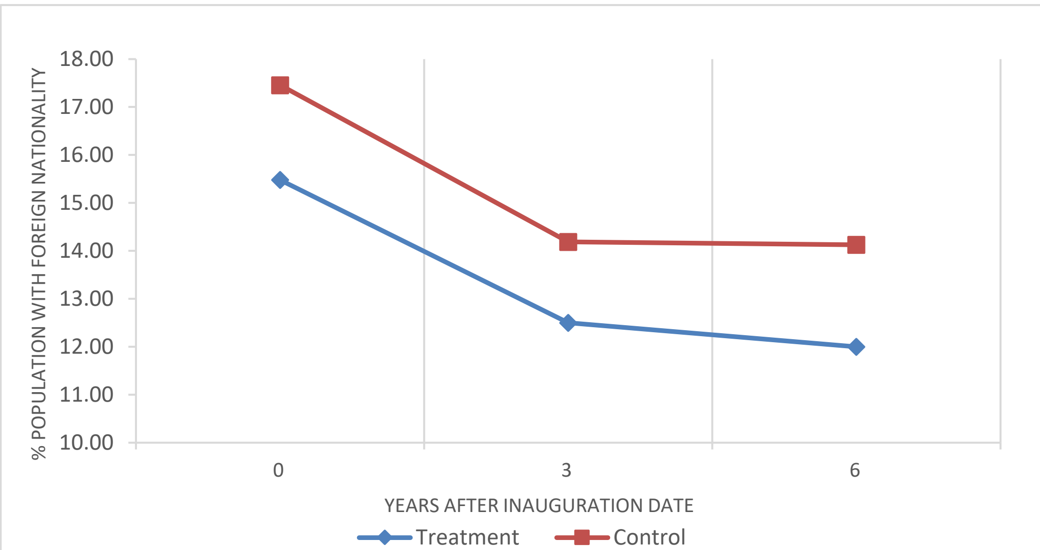
Foreign nationality households may be economically more vulnerable and more likely to move from an area which has been rehabilitated and with higher value. The OLS model (Table 5) still predicts in this case around 80% of the dependent variable's variance but I do not find any statistically significant treatment effect because the path is similar in both groups, even if the percentage of population with foreign nationality decreases over time (Figure 12). The importance of the effect of the baseline value of foreigners in the model is crucial (with a coefficient of -0.168 and significant at the 0.01 level): the higher is the initial level of foreigners in the area the lower is the change of the variable throughout time. (See a more detailed table of the variable changes in the appendix, Table 15).

Table 5. Regression estimates for percentage change of population with foreign nationality

	$FOREIGN_3$	$FOREIGN_6$
Treatment	-0.212 (0.566)	-0.189 (0.836)
baseline	-0.168*** (0.033)	-0.161*** (0.048)
income_mean	1.481* (0.735)	1.778 (1.093)
MA	0.950 (0.621)	2.556*** (0.925)
FV	2.669*** (0.917)	5.265*** (1.226)
Constant	-0.668 (0.717)	0.454 (0.427)
Adjusted R2	0.801	0.776
F-statistic	17.838*** (df = 11; 35)	15.466*** (df = 11; 35)

Note: *p<0.1; **p<0.05; ***p<0.01
Source: own elaboration with data from Madrid City Council

Figure 12. Evolution of % of population with foreign nationality



Source: own elaboration with data from Madrid City Council

6.4. Unemployment rate

The results show a statistically significant treatment effect in the unemployment rate after 6 years of the park's inauguration: being part of the treatment group increase the change in the unemployment rate by 0.858% (Table 6). To interpret this, I compute the weighted average of both groups 6 years after since each park has a different number of observations and computing just a standard average with the values of Table *7* would not be representative. The average change in the treatment group 6 years after is -0.51pp and in the control group is -0.69pp. Putting together the sign of the coefficient of the treatment effect with this weighted average, we interpret that those neighbourhoods near the parks suffer an increase in the change of the unemployment rate, being this change negative; so, unemployment rate was decreasing in these areas and the fact of being treated increases our outcome variable, being less negative. Hence, there is evidence that being located near the park softens the decline of the unemployment rate in contrast to the control group, even if it also experiences a decrease. Therefore, the trend is negative, as we expected, but contrary to my hypothesis, the treatment group suffers a smaller decline than the control group.

The fixed effects corresponding to Miguel Ángel Blanco Gardens and Felipe IV Forest Park are statistically significant both in the short- and medium-term period at 0.05 and 0.01 level; showing the importance of the different effect on the variable of interest depending on the park analysed.

Table 6. Regression estimates for percentage change of the unemployment rate

	$UNEMPLOYMENT_3$	$UNEMPLOYMENT_6$
Treatment	0.416 (0.376)	0.858** (0.337)
dcutoff	0.0004 (0.0003)	0.001** (0.0002)
MA	-2.839*** (0.406)	-2.143*** (0.368)
FV	-4.111*** (0.614)	-1.050** (0.499)
Constant	1.041 (1.038)	0.203 (0.928)
Adjusted R2	0.858	0.645
F-statistic	26.254*** (df = 11; 35)	8.594*** (df = 11; 35)

Note: *p<0.1; **p<0.05; ***p<0.01

Source: own elaboration with data from Madrid City Council

Table 7. Percentage change of the unemployment rate

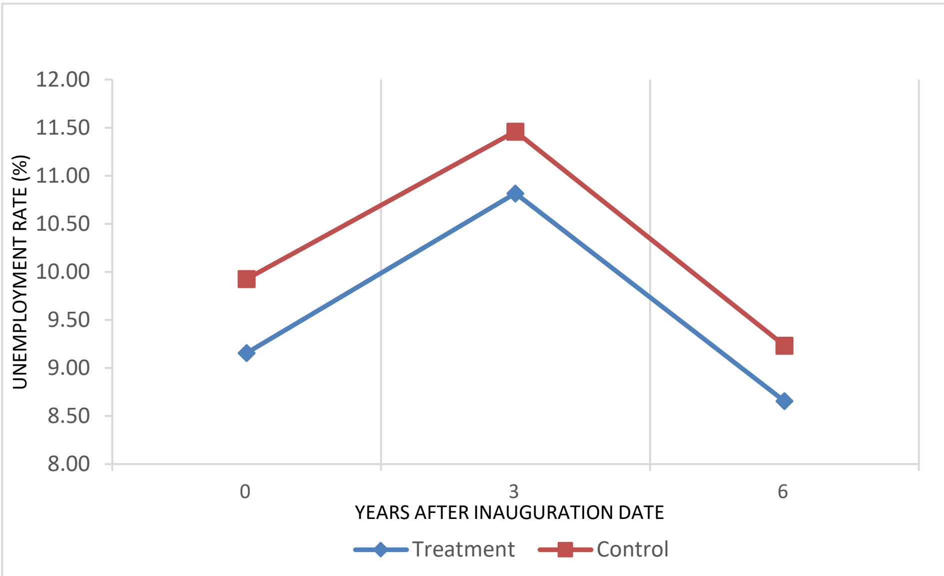
TIME PERIOD	*PARK NAME*	*Avg. change in T*	*Avg. change in C*
3 years after	Madrid Río	2.4 pp	2.4 pp
	Miguel Ángel Blanco Gardens	-1.4 pp	-1.2 pp
	Felipe IV	-1.77 pp	-2.57 pp
	Julio Alguacil Gómez Forest Park	2.7 pp	2.5 pp
	Cuña Verde de O'Donnell & Fuente Carrantona	2.4 pp	2.4 pp
6 years after	Madrid Río	-0.1 pp	-0.3 pp
	Miguel Ángel Blanco Gardens	-2.2 pp	-2.3 pp
	Felipe IV	-1.44 pp	-0.94 pp
	Julio Alguacil Gómez Forest Park	-1 pp	-1.5 pp
	Cuña Verde de O'Donnell & Fuente Carrantona	0 pp	0 pp

Note: T for Treatment and C for control.

Source: own elaboration with data from *Panel de indicadores de distritos y barrios de Madrid. Estudio sociodemográfico - Portal de datos abiertos del Ayuntamiento de Madrid*

The peak found three years after the inauguration in treatment and control can be attributed to the deep economic crisis started in 2007 and whose effects persisted during the years in the first period of our analysis, mainly from 2011 to 2014, but started fading away from 2014 to 2017 (Figure 13).

Figure 13. Evolution of the unemployment rate

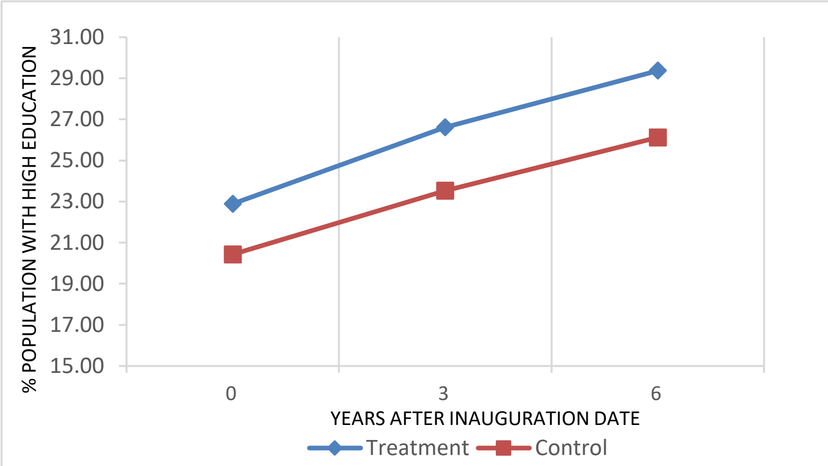


Source: own elaboration with data from Madrid City Council

6.5. Percentage of population with high level education

I expect that those neighbourhoods closer to the park will experience an increase in the population holding a bachelor's degree or any level of high education. Looking at Figure 14 and Table 16 (in the appendix), we do see positive change number in both periods and in both groups, being those in the treatment group somehow a bit larger.

Figure 14. Evolution of the % of population with high education



Source: own elaboration with data from Madrid City Council

Regarding the model, estimates do not show significant evidence of the treatment effect, but they do it on the baseline value variables: the higher is the percentage of people having a high initial level of education the higher is the change of the variable throughout time (those neighbourhoods which have more inhabitants highly educated will experienced a higher increase in the population holding this level of education).

Table 8. Regression estimates for the percentage change of population with high education

	$HEDUC_3$	$HEDUC_6$
Treatment	0.695 (0.746)	0.164 (1.047)
baseline	0.123*** (0.035)	0.213*** (0.049)
MA	-4.231*** (0.962)	-4.130*** (1.334)
POP	-0.031 (0.023)	-0.061** (0.026)
Constant	0.304 (0.790)	0.831 (1.145)
Adjusted R2	0.510	0.584
F-statistic	5.360*** (df = 11; 35)	6.871*** (df = 11; 35)

Note: *p<0.1; **p<0.05; ***p<0.01.

Source: own elaboration with data from Madrid City Council

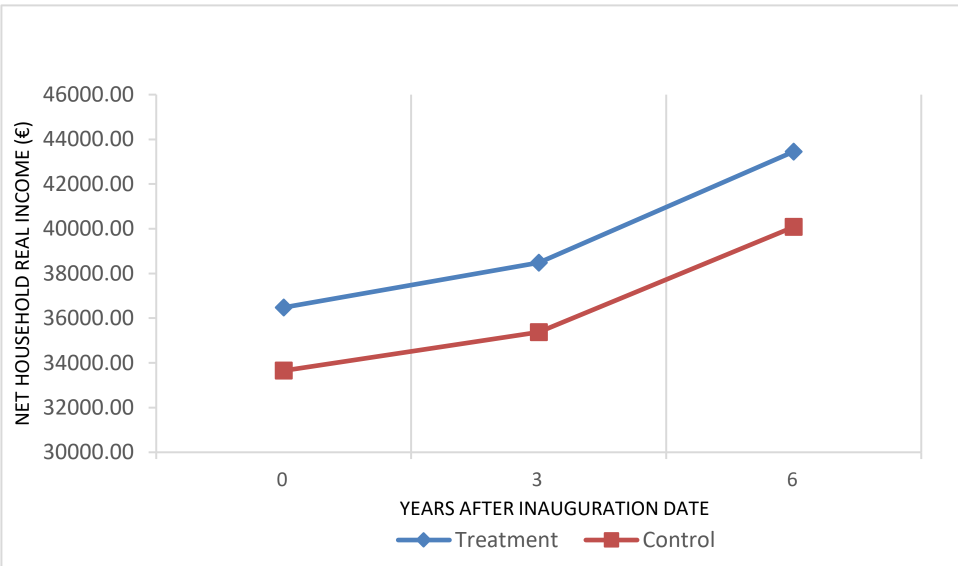
The model explains around 65% of the variance of the outcome variable (Table 8).

6.6. Annual real net household income

A clear indicator of gentrification is the increase in the income of the population living in the treated area, around the green parks. By first looking to Figure 15, we can see an increase in the level of net income throughout time but in a parallel trend treatment and control units, being the treatment group a bit richer -which does not matter in my research since we only care about the change in income, not the actual absolute level-.

The OLS model evidences significant and interesting results. Treatment effect after 3 and 6 years is statistically significant at the 0.05 and 0.01 level respectively and negative, -3.775 and -7.769 (Table 10). As I have proceeded with another variable, I should compute again the weighted average changes through the values displayed in Table 9. Since I am only interested on the sign of the change to interpret the treatment effect and all values in the table are positive there is no need to do it. Contrary to what we would expect, being treated (located less than 1021 meters from the park) is going to decrease the change of the level of income: incomes for all neighbourhoods in the treatment group increase by less, and it does not matter based on the distance from the park, given that *dcutoff* + *dcutoff:Treatment* is almost 0.

Figure 15. Evolution of annual real net household income



Source: own elaboration with data from Madrid City Council

Table 9. Change (%) in the annual real net household income

TIME PERIOD	*PARK NAME*	*Avg. change in T*	*Avg. change in C*
3 years after	Madrid Río	6.1 %	5.7 %
	Miguel Ángel Blanco Gardens	5.3 %	5.7 %
	Felipe IV	7.68 %	9.62 %
	Julio Alguacil Gómez Forest Park	5.24 %	7.08 %
	Cuña Verde de O'Donnell & Fuente Carrantona	3.5 %	3.7 %
6 years after	Madrid Río	23.3 %	22.7 %
	Miguel Ángel Blanco Gardens	13.7 %	16.8 %
	Felipe IV	14.35 %	15.91 %
	Julio Alguacil Gómez Forest Park	23.73 %	28.27 %
	Cuña Verde de O'Donnell & Fuente Carrantona	17.3 %	18 %

Note: T for Treatment and C for control. Source: own elaboration with data from *Panel de indicadores de distritos y barrios de Madrid. Estudio sociodemográfico - Portal de datos abiertos del Ayuntamiento de Madrid*

Another interesting insight is the statistically significant effect of the variable *dcutoff*. An increase in this variable will decrease the change in income: for the control group, the income grows slower the further they are away from the park. So, summing up, in the treatment group the income grows slower than in the control group regardless of the distance from the park; whereas in the control group, the further away they are located, the lower is the increase. Moreover, I should remark the positive effect of the variable *d2011*, involving Madrid Río and Julio Alguacil Gómez Forest Park, inaugurated in 2011, on my variable of interest. Unfortunately, annual real net household income is the variable whose variance is the less explained by our models, just an adjusted R^2 equal to 22.3% and 43.7% after 3 and 6 years, respectively.

Table 10. Regression estimates for the change in the annual real net household income

	$RINCOME_3$	$RINCOME_6$
dcutoff	-0.004*** (0.001)	-0.008*** (0.002)
treatment	-3.775** (1.553)	-7.769*** (2.717)
d2011	3.431*** (1.227)	7.240*** (2.146)
MA	3.717** (1.810)	2.115 (3.167)
FV	5.485** (2.383)	-1.105 (4.169)
constant	26.039 (20.416)	83.773** (35.719)
Adjusted R2	0.223	0.437
F-statistic	2.646** (df = 8; 38)	5.458*** (df = 8; 38)

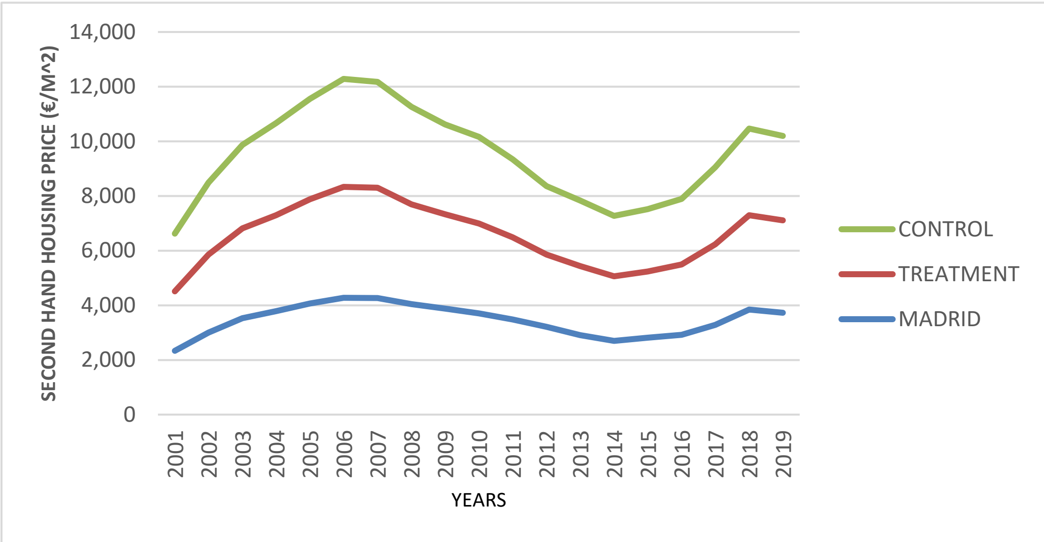
Note: *p<0.1; **p<0.05; ***p<0.01

Source: own elaboration with data from Madrid City Council

6.7. Second-hand housing real prices (€/m^2)

Before explaining the results of the model, I plot in Figure 16 the evolution of housing prices in Madrid and in my treatment and control groups since 2001. I think it is interesting to look at the evolution of prices way before the creation of the park because, in addition to the data availability, its impact on the closest neighbourhoods probably started before the official opening year, especially in Madrid Río due to its larger scale. We see than in the three cases (treatment, control, and the entire city), the prices' peak coincides around 2006 and 2007 and decreases until 2014, moment when it starts to recover again. This recent trend can also be seen in Figure 19.

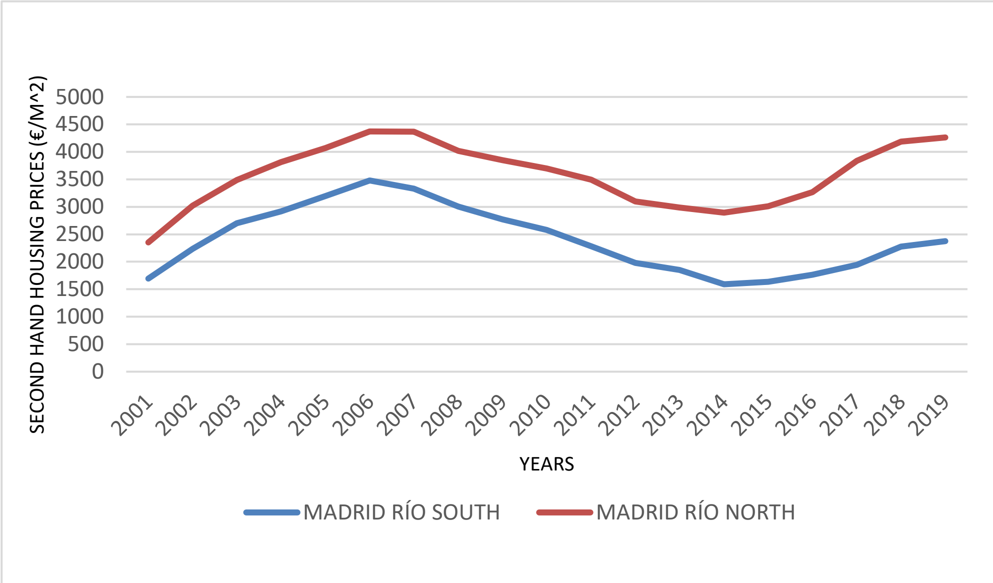
Figure 16. Evolution of second-hand housing nominal prices (€/m^2)



Source: own elaboration with data from Madrid City Council

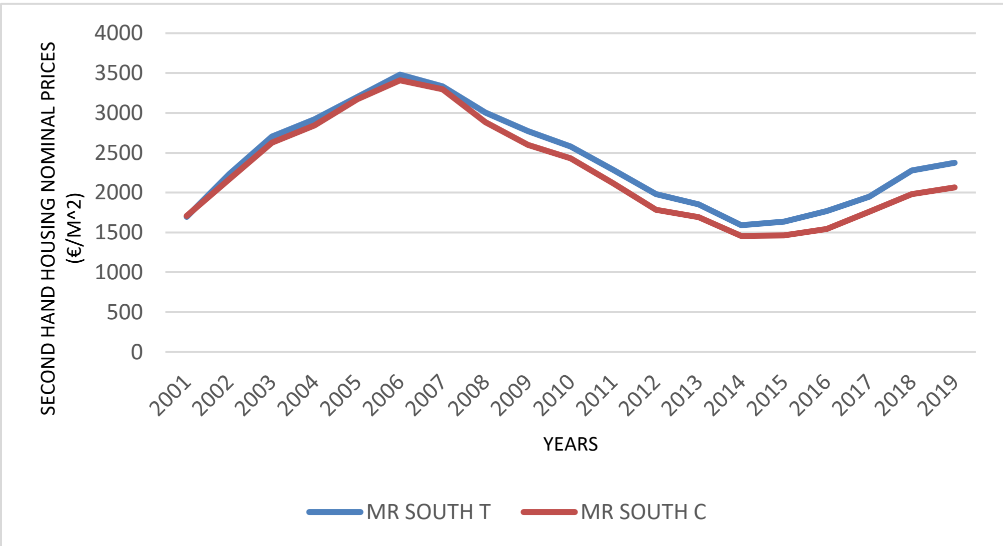
Figure 17 shows that, even that the treated neighbourhoods at the north of Madrid Río are richer and less vulnerable than those treated at the south, they follow a similar trend across time in terms of prices ups and downs. And focusing on the southern region of Madrid Río, I plot any differences in trends between our treatment and control group. We do not see any relevant difference at first sight (Figure 18).

Figure 17. Evolution of second-hand housing nominal prices (€/m^2) in Madrid Río



Source: own elaboration with data from Madrid City Council

Figure 18. Evolution of second-hand housing nominal prices (€/m^2) in Madrid Río South



Source: own elaboration with data from Madrid City Council

Going back to my analysis, we would expect a rise in the second-hand housing prices in the treatment neighbourhoods due to the area's increase in value brought by the creation of a green amenity. The second-hand housing is a good market to analyse because any displacement of inhabitants will be from those that move away from an existing house, not from a new one. I find a statistically significant treatment effect of -16.379 at the 0.01 level after 6 years of the parks' inauguration (Table 12). To interpret the results, I compute the weighted average of the averages changes in treatment of Table 11 (after 6 years), that is 4.03. Combining the information which states that the price change is positive, meaning that increases, with the fact that the coefficient of the treatment effect is negative, I can unexpectedly conclude that those neighbourhoods near the park experienced a smaller increase in prices than those in the control group.

Also play a key role in explaining the outcome variable, the dummies MA and FV as well as the baseline values of the prices, whose coefficients are 16.795 after 3 years and 47.859 after 6 years. Having higher initial values in housing prices increases the magnitude of the positive changes in those neighbourhoods compared to those which start at a lower level.

This model explains 89.2% (after 3 years) and 78.6% (after 6 years) of the variation of the outcome variable.

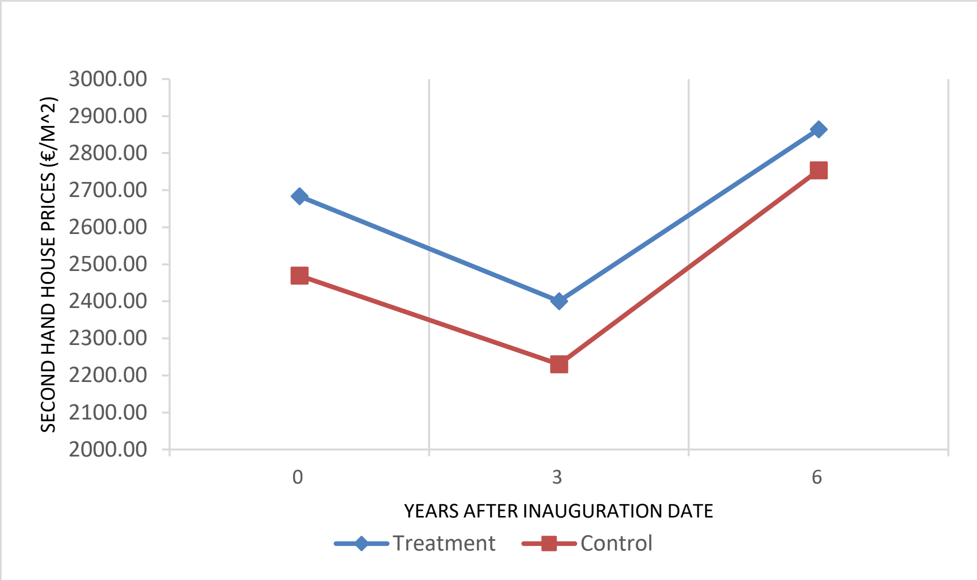
Table 11. Change (%) in second-hand housing real prices (€/m^2)

TIME PERIOD	*PARK NAME*	*Avg. change in T*	*Avg. change in C*
3 years after	Madrid Río	-20.3 %	-22.8 %
	Miguel Ángel Blanco Gardens	16.1 %	17.3 %
	Felipe IV	30.51 %	18.3 %
	Julio Alguacil Gómez Forest Park	-18.83 %	-27.47 %
	Cuña Verde de O'Donnell & Fuente Carrantona	-20.6 %	-20.8 %
6 years after	Madrid Río	-0.3 %	-3.6 %
	Miguel Ángel Blanco Gardens	28.6 %	30.9 %
	Felipe IV	37.13 %	43.71 %
	Julio Alguacil Gómez Forest Park	-11.13 %	
	Cuña Verde de O'Donnell & Fuente Carrantona	-3.7 %	-1.8 %

Note: T for Treatment and C for control.

Source: own elaboration with data from *Panel de indicadores de distritos y barrios de Madrid. Estudio sociodemográfico - Portal de datos abiertos del Ayuntamiento de Madrid*

Figure 19. Evolution of second-hand housing real prices



Source: own elaboration with data from Madrid City Council

Table 12. Regression estimates for the change in second-hand housing real prices

	$RPRICE_3$	$RPRICE_6$
dcutoff	-0.004 (0.003)	-0.010** (0.004)
treatment	-5.078 (3.465)	-16.379*** (5.420)
baseline	16.795*** (6.066)	47.859*** (9.328)
MA	30.720*** (3.849)	25.940*** (5.861)
FV	42.545*** (5.003)	38.702*** (7.644)
constant	-149.628*** (46.968)	-364.005*** (72.156)
Adjusted R2	0.892	0.786
F-statistic	35.847*** (df = 10; 32)	16.043*** (df = 10; 31)

Note: *p<0.1; **p<0.05; ***p<0.01

Source: own elaboration with data from Madrid City Council

7. DISCUSSION

In this study, I wanted to assess whether there exists a causal relationship between the opening of green urban parks in the city of Madrid and the process of gentrification in the areas surrounding them in the period between 2009 and 2015. Through a Geographic Regression Discontinuity design, I have been able to assign the treatment or control condition to each of the neighbourhoods under analysis based on their distance to their closest park's boundary.

Regression results only reveal a significant treatment effect for the following variables: the unemployment rate six years after the park's inauguration, the annual net household income three and six years after, and the second-hand housing real prices three and six years later. The unemployment rate decreases in both treatment and control groups, and the treatment effect is reflected in a smaller decrease in the unemployment rate in those neighbourhoods near the park rather than a more significant decrease, which would be an indicator of a gentrifying trend. Regarding the income indicator, households' incomes in the treatment neighbourhoods increase by less than those in the control group. But also, those control neighbourhoods located further away from the park experience a slower increase compared to those closer to the cut-off. Lastly, housing prices after six years have increased in both groups but to a lesser extent in the treatment group.

Regarding the other indicators, apart from not showing a statistically significant treatment effect, they follow a similar trend in the treatment and control groups. The proportion of the population with foreign nationality decreases in both groups, and the percentage of those with high education increases in both cases. Even surprisingly, the percentage of those over 65 living alone increases no matter their neighbourhood's treatment or control condition.

It is important to note that other projects may have accompanied or justified such sociodemographic and economic changes. For instance, the Manzanares River revitalization project started way before Madrid Río's inauguration, and its effects in terms of housing values should be observed not from 2011 onwards but rather after 2003. I also consider it appropriate to mention the community involvement during the Madrid Río project because, as McKendry and Janos (2015) introduced, active participation should play a role in greening initiatives. According to the City Council of Madrid (Habitat.aq.upm.es, 2015), citizen participation has been a critical factor in developing all actions related to the Madrid Río project since its beginning. During the 2003-2007 period, eleven informative points were established throughout the entire reform of the M-30 bypass road in which citizens were free to ask any inquiry. Moreover, a contest took place in September 2005 to involve children and young people in the project by asking for proposals that were primarily included in the final solution of the plan. The City Council prioritized the preferences and needs of the southeast districts of Madrid, and the team responsible for the project undertook a detailed analysis of specific requests received from the population. Therefore, this is a potential explanation of why our results differ from those that should be observed if green gentrification occurs.

There is no evidence that the magnitude of the treatment effect is related to the income level position of a particular neighbourhood relative to the income mean's city, even if this phenomenon occurs in vulnerable and working-class quartiers. Poor communities, especially those in the south of Madrid Río, likely have not experienced an increase in the area's quality and value enough to attract potential gentrifiers (Anguelovski et al., 2018). The socio-spatial polarization that characterizes the city of Madrid (see Section 3) is not a recent phenomenon but a long-established feature that has accompanied the city since decades ago; the discrimination towards southern neighbourhoods is too rooted in people's minds for higher income classes to show an interest for this area.

8. CONCLUSIONS

This paper contributes to the literature on green gentrification by using a Geographic Regression Discontinuity design to find a causal relationship between urban green parks and gentrifying trends. Based on the literature review conducted, I have yet to see any previous studies on green gentrification that employ the exact methodology used in this research. Hence, I add to the developing body of Geographic Regression Discontinuity designs its application to green gentrification studies as a methodological tool. The contribution has also been made in terms of the geographical area of study. There was a gap in the green gentrification quantitative studies conducted in the capital of Spain, Madrid, which may inspire further exploration in more European cities.

Based on the stated goal of this research, the findings strongly support the conclusion that there is not causal effect between creating new green parks and the dependent variables attributed to gentrifying trends. Except for the percentage of the population over 65 living alone, the other indicators are going in the direction I hypothesized in the introduction, especially after six years from the opening. Still, its effects on the treatment group compared to those on the control group do not allow me to identify green gentrification.

While realizing this thesis, I encountered different limitations that have influenced the quality and robustness of the results. The primary constraint of the study has been data limitations in terms of time, unit of analysis, and spatial coverage.

Having more years in which data for each of the gentrification indicators was publicly available would have enabled me to realize a long-term analysis and introduce new parks into the study, the ones inaugurated before 2009. Moreover, the City Council of Madrid provides a more homogenous and more affluent database from different indicators than other Spanish city councils. My initial idea was to perform the study across different Spanish cities, but the data available was too heterogeneous to pool it together into the same analysis.

This study's analysis unit was the smallest unit for which data was publicly available, the neighbourhood level, an important caveat of the paper. The same research, when conducted with census tracts as units of analysis, would improve the study's statistical power, yielding more precise estimates. This would facilitate the generalization of the results to other contexts and provide a more consistent contribution to economic policy. A direct implication of working with smaller units of analysis in this research would be the establishment of a more accurate cut-off in my methodology. I would no longer need a broader buffer to include the nearest centroids but a more realistic one that considers the distance at which the effects of the park should be observed - much closer than 1,021 meters from the green area. I would have more observations near the cut-off, allowing me to observe the behaviour of the data near both sides of that threshold. I also suggest implementing a local regression, the triangular kernel (Huntington-Klein, 2021), in which the weight you assign to each observation increases closer to the cut-off. In this way, we could test if the proximity to the park explains gentrification around them (Anguelovski et al., 2018).

The previous caveats motivate new challenges and opportunities for future gentrification research. Working with smaller units of analysis would allow us to compare observations for different parks to find if, for instance, the functionality or size of the park analysed plays a role in the gentrification process. In this study, the scarcity of data forced me to pool all observations together without disentangling the effect of each of the parks separately. I would also suggest to conduct comparative studies between cities (also from outside Europe and the USA) to identify additional factors that contribute to the emergence of gentrification in the studied regions. The methodology employed in this research represents its first application in the field of green gentrification, and it can serve as a precedent for future researchers to use this quasi-experimental strategy across many other areas.

Green gentrification talks about equality, rights, and justice but also about environmental protection, climate change, and sustainable development. Green gentrification affects society, from the most vulnerable communities to the wealthiest institutions, city councils, and urban planners. The interdisciplinarity nature of the concept suggests a wide range of policy implications that should be considered in the planning of any green urban project. We should analyse the economic consequences and other impacts of green practices before starting their development. Additionally, the focus should be extended beyond the objective of mitigating climate change to consider how we will achieve that goal and its impacts on the surrounding area. There is a trade-off between equality and environmental protection. Still, the first step is acknowledging its existence and finding the tools to help alleviate any adverse effects. Further research is needed to have the knowledge that will allow us to address each specific context effectively.

9. REFERENCES

Anguelovski, I., Connolly, J. J. T., Cole, H., Garcia-Lamarca, M., Triguero-Mas, M., Baró, F., Martin, N., Conesa, D., Shokry, G., del Pulgar, C. P., Ramos, L. A., Matheney, A., Gallez, E., Oscilowicz, E., Máñez, J. L., Sarzo, B., Beltrán, M. A., & Minaya, J. M. (2022). Green gentrification in European and North American cities. *Nature Communications*, *13*(1), Article 1. https://doi.org/10.1038/s41467-022-31572-1

Anguelovski, I., Connolly, J. J. T., Masip, L., & Pearsall, H. (2018). Assessing green gentrification in historically disenfranchised neighborhoods: A longitudinal and spatial analysis of Barcelona. *Urban Geography*, *39*(3), 458–491. https://doi.org/10.1080/02723638.2017.1349987

Ayuntamiento de Madrid. (2018). *Plan de Infraestructura Verde y Biodiversidad—Portal de transparencia del Ayuntamiento de Madrid*. https://transparencia.madrid.es/portales/transparencia/es/Organizacion/Planes-y-memorias/Planes/Plan-de-Infraestructura-Verde-y-Biodiversidad/?vgnextfmt=default&vgnextoid=5fdec0f221714610VgnVCM2000001f4a900aRCRD&vgnextchannel=d869508929a56510VgnVCM1000008a4a900aRCRD

Ayuntamiento de Madrid | Banco de datos de Madrid. (n.d.). Retrieved 25 May 2023, from https://www-s.madrid.es/CSEBD_WBINTER/arbol.html

Burgos&Garrido Arquitectos. (n.d.). *MADRID RÍO*. Burgos & Garrido. Retrieved 25 May 2023, from https://burgos-garrido.com/project/madrid-rio/

Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs. *Econometrica*, *82*(6), 2295–2326. https://doi.org/10.3982/ECTA11757

Card, D., & Krueger, A. B. (1993). *Minimum Wages and Employment: A Case Study of the Fast Food Industry in New Jersey and Pennsylvania* (Working Paper No. 4509). National Bureau of Economic Research. https://doi.org/10.3386/w4509

Checker, M. (2011). *Wiped Out by the "Greenwave": Environmental Gentrification and the Paradoxical Politics of Urban Sustainability—CHECKER - 2011—City & Society—Wiley Online Library*. https://anthrosource.onlinelibrary.wiley.com/doi/full/10.1111/j.1548-744X.2011.01063.x

City Council of Madrid. (2007). *Inicio—Ayuntamiento de Madrid*. https://www.madrid.es/portal/site/munimadrid

Dale, A., & Newman, L. (2009). *Full article: Sustainable development for some: Green urban development and affordability*. https://www.tandfonline.com/doi/full/10.1080/13549830903089283

Dooling, S. (2009). *Ecological Gentrification: A Research Agenda Exploring Justice in the City—DOOLING - 2009—International Journal of Urban and Regional Research—Wiley Online Library*. https://onlinelibrary.wiley.com/doi/full/10.1111/j.1468-2427.2009.00860.x

European Environment Agency. (2022). *Who benefits from nature in cities? Social inequalities in access to urban green and blue spaces across Europe — European Environment Agency* [Briefing]. https://www.eea.europa.eu/publications/who-benefits-from-nature-in

Glass, R. (1964). *WordPress.com: Build a Site, Sell Your Stuff, Start a Blog & More*. WordPress.Com. https://wordpress.com/

Gobierno de España. (2017). El proyecto. *Restauración del Manzanares en El Pardo*. https://restauracionfluvialriomanzanares.es/el-proyecto/

Goodling, E., Green, J., & McClintock, N. (2015). Uneven development of the sustainable city: Shifting capital in Portland, Oregon. *Urban Geography*, *36*(4), 504–527. https://doi.org/10.1080/02723638.2015.1010791

Goossens, C., Oosterlynck, S., & Bradt, L. (2020). *Livable streets? Green gentrification and the displacement of longtime residents in Ghent, Belgium*.

Gould, K., & Tammy, L. (2016). *Green Gentrification: Urban sustainability and the struggle for environmental justice*. Routledge. https://doi.org/10.4324/9781315687322

Habitat.aq.upm.es, B. C. (2015). *Madrid Río*. http://habitat.aq.upm.es/dubai/14/bp-52.html

Huntington-Klein. (2021). *Chapter 20—Regression Discontinuity | The Effect*. https://theeffectbook.net/ch-RegressionDiscontinuity.html

Immergluck, D., & Balan, T. (2018). Sustainable for whom? Green urban development, environmental gentrification, and the Atlanta Beltline. *Urban Geography*, *39*(4), 546–562. https://doi.org/10.1080/02723638.2017.1360041

INE. (n.d.). *Indicadores Urban Audit para Áreas Submunicipales (2013)(13925)*. INE. Retrieved 27 May 2023, from https://www.ine.es/jaxiT3/Tabla.htm?t=13925&L=0

Keele, L., Titiunik, R., & Zubizarreta, J. R. (2015). Enhancing a Geographic Regression Discontinuity Design Through Matching to Estimate the Effect of Ballot Initiatives on Voter Turnout. *Journal of the Royal Statistical Society Series A: Statistics in Society*, *178*(1), 223–239. https://doi.org/10.1111/rssa.12056

Kotsila, P., Anguelovski, I., García-Lamarca, M., & Sekulova, F. (2023). *Injustice in Urban Sustainability | Ten Core Drivers | Panagiota Kotsila*. https://www.taylorfrancis.com/books/oa-mono/10.4324/9781003221425/injustice-urban-sustainability-panagiota-kotsila-isabelle-anguelovski-filka-sekulova-melissa-garc%C3%ADa-lamarca

Kwon, Y., Joo, S., Han, S., & Park, C. (2017). Mapping the Distribution Pattern of Gentrification near Urban Parks in the Case of Gyeongui Line Forest Park, Seoul, Korea. *Sustainability*, *9*(2), Article 2. https://doi.org/10.3390/su9020231

Lancee, B., & Van de Werfhorst, H. G. (2012). Income inequality and participation: A comparison of 24 European countries. *Social Science Research*, *41*(5), 1166–1178. https://doi.org/10.1016/j.ssresearch.2012.04.005

Lee, D. S. (2008). Randomized experiments from non-random selection in U.S. House elections. *Journal of Econometrics*, *142*(2), 675–697. https://doi.org/10.1016/j.jeconom.2007.05.004

Lowes, S., Nunn, N., Robinson, J., & Weigel, J. (2017). *The Evolution of Culture and Institutions: Evidence From the Kuba Kingdom—Lowes—2017—Econometrica—Wiley Online Library*. https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA14139

Lubitow, A., & Miller, T. (2013). Contesting Sustainability: Bikes, Race, and Politics in Portlandia. *Environmental Justice*, *6*, 121–126. https://doi.org/10.1089/env.2013.0018

Marche, G. (2015). What Can Urban Gardening Really Do About Gentrification? A Case-Study of Three San Francisco Community Gardens. *European journal of American studies*, *10*(3), Article 3. https://doi.org/10.4000/ejas.11316

McKendry, C., & Janos, N. (2015). Greening the industrial city: Equity, environment, and economic growth in Seattle and Chicago. *International Environmental Agreements: Politics, Law and Economics*, *15*. https://doi.org/10.1007/s10784-014-9267-0

Medio Ambiente y Movilidad, A. de M. (2021). *Parques y jardines—Ayuntamiento de Madrid*. https://www.madrid.es/portales/munimadrid/es/Inicio/Medio-ambiente/Parques-y-jardines/?vgnextfmt=default&vgnextchannel=2ba279ed268fe410VgnVCM1000000b205a0aRCRD

Montgomery, A. (2016). *Reappearance of the Public: Placemaking, Minoritization and Resistance in Detroit—Montgomery—2016—International Journal of Urban and Regional Research—Wiley Online Library*. https://onlinelibrary.wiley.com/doi/full/10.1111/1468-2427.12417

Orueta, F. D., & Seoane, M. L. L. (2012). *SUBURBANIZACIÓN Y CAMBIO SOCIAL EN LA METRÓPOLI MADRILEÑA SUBURBANISM AND SOCIAL CHANGE IN MADRID METROPOLIS*.

Panel de indicadores de distritos y barrios de Madrid. Estudio sociodemográfico—Portal de datos abiertos del Ayuntamiento de Madrid. (n.d.). Retrieved 25 May 2023, from https://datos.madrid.es/portal/site/egob/menuitem.c05c1f754a33a9fbe4b2e4b284f1a5a0/?vgnextoid=71359583a773a510VgnVCM2000001f4a900aRCRD&vgnextchannel=374512b9ace9f310VgnVCM100000171f5a0aRCRD&vgnextfmt=default

Preteceille, E. (2000). Segregation, class and politics in large cities. In A. Bagnasco & P. Le Galès (Eds.), *Cities in Contemporary Europe* (pp. 74–97). Cambridge University Press. https://doi.org/10.1017/CBO9780511558733.005

Quastel, N. (2009). *Political Ecologies of Gentrification: Urban Geography: Vol 30, No 7*. https://www.tandfonline.com/doi/abs/10.2747/0272-3638.30.7.694

Quinton, J., Nesbitt, L., & Sax, D. (2022). How well do we know green gentrification? A systematic review of the methods. *Progress in Human Geography*, *46*(4), 960–987. https://doi.org/10.1177/03091325221104478

Rigolon, A., & Németh, J. (2020). *Green gentrification or 'just green enough': Do park location, size and function affect whether a place gentrifies or not? - Alessandro Rigolon, Jeremy Németh, 2020*. https://journals.sagepub.com/doi/10.1177/0042098019849380

Safransky, S. (2014). Greening the urban frontier: Race, property, and resettlement in Detroit. *Geoforum*, *56*, 237–248. https://doi.org/10.1016/j.geoforum.2014.06.003

Tomàs, M., Subirats, J., Iglesias, M., & Martí-Costa, M. (2011). *Políticas urbanas en España. Grandes ciudades, actores, gobiernos locales*.

UNDESA. (2020). *UNDESA World Social Report 2020 | DISD*. https://www.un.org/development/desa/dspd/world-social-report/2020-2.html

United Nations. (1987). *Home | Sustainable Development*. https://sdgs.un.org/

United Nations. (2015). *THE 17 GOALS | Sustainable Development*. https://sdgs.un.org/goals

Wolch, J., Byrne, J., & Newell, J. (2014). Urban green space, public health, and environmental justice: The challenge of making cities `just green enough'. *Landscape Urban Plann*, *125*. https://doi.org/10.1016/j.landurbplan.2014.01.017

10. APPENDIX

Table 13. Percentage change of population older than 65

TIME PERIOD	*PARK NAME*	*Avg. change in T*	*Avg. change in C*
3 years after	Madrid Río	0.9 pp	1.1 pp
	Miguel Ángel Blanco Gardens	0.1 pp	1.3 pp
	Felipe IV	0.6 pp	0.6 pp
	Julio Alguacil Gómez Forest Park	0.1 pp	0.6 pp
	Cuña Verde de O'Donnell & Fuente Carrantona	1.46 pp	1.8 pp
6 years after	Madrid Río	1.19 pp	1.3 pp
	Miguel Ángel Blanco Gardens	0.6 pp	1.7 pp
	Felipe IV	1 pp	0.3 pp
	Julio Alguacil Gómez Forest Park	-0.3 pp	0.2 pp
	Cuña Verde de O'Donnell & Fuente Carrantona	2.28 pp	2.58 pp

Note: T for Treatment and C for control.

Source: own elaboration with data from *Panel de indicadores de distritos y barrios de Madrid. Estudio sociodemográfico - Portal de datos abiertos del Ayuntamiento de Madrid*

Table 14. Percentage change of population over 65 living alone

TIME PERIOD	*PARK NAME*	*Avg. change in T*	*Avg. change in C*
3 years after	Madrid Río	0.5 pp	0.4 pp
	Miguel Ángel Blanco Gardens	0.275 pp	0.45 pp
	Felipe IV	0.1 pp	14.6 pp
	Julio Alguacil Gómez Forest Park	0.3 pp	0.3 pp
	Cuña Verde de O'Donnell & Fuente Carrantona	0.6 pp	0.4 pp
6 years after	Madrid Río	0.6 pp	0.6 pp
	Miguel Ángel Blanco Gardens	0.325 pp	0.7 pp
	Felipe IV	0.3 pp	15.5 pp
	Julio Alguacil Gómez Forest Park	0.3 pp	0.4 pp
	Cuña Verde de O'Donnell & Fuente Carrantona	1.3 pp	1.025 pp

Note: T for Treatment and C for control.

Source: own elaboration with data from *Panel de indicadores de distritos y barrios de Madrid. Estudio sociodemográfico - Portal de datos abiertos del Ayuntamiento de Madrid*

Table 15. Percentage change of population with foreign nationality

TIME PERIOD	***PARK NAME***	***Avg. change in T***	***Avg. change in C***
3 years after	Madrid Río	-4.2 pp	-4.6 pp
	Miguel Ángel Blanco Gardens	-0.7 pp	-0.4 pp
	Felipe IV	0.9 pp	0 pp
	Julio Alguacil Gómez Forest Park	-1.4 pp	-3.3 pp
	Cuña Verde de O'Donnell & Fuente Carrantona	-2.4 pp	-3.1 pp
6 years after	Madrid Río	-5.3 pp	-5.4 pp
	Miguel Ángel Blanco Gardens	0.3 pp	1.2 pp
	Felipe IV	2.4 pp	2.2 pp
	Julio Alguacil Gómez Forest Park	-0.9 pp	-2.5 pp
	Cuña Verde de O'Donnell & Fuente Carrantona	-3 pp	-3.4 pp

Note: T for Treatment and C for control.

Source: own elaboration with data from *Panel de indicadores de distritos y barrios de Madrid. Estudio sociodemográfico - Portal de datos abiertos del Ayuntamiento de Madrid*

Table 16. Percentage change of population with high education

TIME PERIOD	***PARK NAME***	***Avg. change in T***	***Avg. change in C***
3 years after	Madrid Río	4.1 pp	3.6 pp
	Miguel Ángel Blanco Gardens	3.3 pp	2.8 pp
	Felipe IV	3.7 pp	1.8 pp
	Julio Alguacil Gómez Forest Park	1.4 pp	1.7 pp
	Cuña Verde de O'Donnell & Fuente Carrantona	3.4 pp	2.5 pp
6 years after	Madrid Río	6.9 pp	6 pp
	Miguel Ángel Blanco Gardens	7.4 pp	6.9 pp
	Felipe IV	6.2 pp	5.5 pp
	Julio Alguacil Gómez Forest Park	2.2 pp	2.4 pp
	Cuña Verde de O'Donnell & Fuente Carrantona	5.4 pp	4.5 pp

Note: T for Treatment and C for control.

Source: own elaboration with data from *Panel de indicadores de distritos y barrios de Madrid. Estudio sociodemográfico - Portal de datos abiertos del Ayuntamiento de Madrid*

	alone_65_3
dcutoff	0.0001 (0.0002)
TREATMENT	0.307 (0.221)
d2011	-0.131 (0.159)
baseline_alone_65	-0.101* (0.058)
income_mean	0.444* (0.237)
MA	0.178 (0.237)
FV	3.213*** (0.357)
JA	0.247 (0.296)
POP_3	-0.160*** (0.007)
dcutoff:TREATMENT	0.0001 (0.0003)
TREATMENT:income_mean	-0.151 (0.258)
Constant	0.156 (0.297)
Observations	47
R2	0.974
Adjusted R2	0.966
Residual Std. Error	0.383 (df = 35)
F Statistic	121.105*** (df = 11; 35)

	alone_65_6
dcutoff	0.0002 (0.0002)
TREATMENT	0.405 (0.319)
d2011	-0.030 (0.236)
baseline_alone_65	-0.154* (0.086)
income_mean	0.731** (0.343)
MA	0.413 (0.350)
FV	5.552*** (0.458)
JA	0.185 (0.427)
POP_6	-0.137*** (0.008)
dcutoff:TREATMENT	0.0003 (0.0005)
TREATMENT:income_mean	-0.280 (0.374)
Constant	0.454 (0.427)
Observations	47
R2	0.952
Adjusted R2	0.938
Residual Std. Error	0.552 (df = 35)
F Statistic	63.784*** (df = 11; 35)

	FOREIGN_3
dcutoff	-0.001 (0.0004)
TREATMENT	-0.212 (0.566)
d2011	0.129 (0.497)
baseline_foreign	-0.168*** (0.033)
MA	0.950 (0.621)
FV	2.669*** (0.917)
JA	0.427 (0.856)
POP_3	-0.005 (0.017)
income_mean	1.481* (0.735)
dcutoff:TREATMENT1	0.001 (0.001)
TREATMENT1:income_mean	-0.852 (0.665)
Constant	-0.668 (0.717)
Observations	47
R2	0.849
Adjusted R2	0.801
Residual Std. Error	1.006 (df = 35)
F Statistic	17.838*** (df = 11; 35)

Note: *p<0.1; **p<0.05; ***p<0.01

	FOREIGN_6
dcutoff	-0.001 (0.001)
TREATMENT	-0.189 (0.836)
d2011	-0.381 (0.740)
baseline_foreign	-0.161*** (0.048)
MA	2.556*** (0.925)
FV	5.265*** (1.226)
JA	1.991 (1.267)
POP_6	-0.003 (0.020)
income_mean	1.778 (1.093)
dcutoff:TREATMENT	0.001 (0.001)
TREATMENT1:income_mean	-1.220 (0.982)
Constant	-1.149 (1.078)
Observations	47
R2	0.829
Adjusted R2	0.776
Residual Std. Error	1.487 (df = 35)
F Statistic	15.466*** (df = 11; 35)

	UNEMPLOYMENT_3
dcutoff	0.0004 (0.0003)
TREATMENT	0.416 (0.376)
d2011	-0.125 (0.278)
baseline_unemployment	0.134 (0.094)
MA	-2.839*** (0.406)
FV	-4.111*** (0.614)
JA	-0.644 (0.639)
POP_3	0.018 (0.011)
income_mean	-0.717 (0.564)
dcutoff:TREATMENT	-0.001 (0.001)
TREATMENT1:income_mean	-0.272 (0.448)
Constant	1.041 (1.038)
Observations	47
R2	0.892
Adjusted R2	0.858
Residual Std. Error	0.676 (df = 35)
F Statistic	26.254*** (df = 11; 35)

	UNEMPLOYMENT_6
dcutoff	0.001** (0.0002)
TREATMENT	0.858** (0.337)
d2011	-0.353 (0.252)
baseline_unemployment	-0.060 (0.084)
MA	-2.143*** (0.368)
FV	-1.050** (0.499)
JA	-0.918 (0.574)
POP_6	-0.003 (0.008)
income_mean	-0.283 (0.506)
dcutoff:TREATMENT	-0.0004 (0.001)
TREATMENT1:income_mean	-0.320 (0.402)
Constant	0.203 (0.928)
Observations	47
R2	0.730
Adjusted R2	0.645
Residual Std. Error	0.607 (df = 35)
F Statistic	8.594*** (df = 11; 35)

Note: *p<0.1; **p<0.05; ***p<0.01

	HEDUC_3
dcutoff	0.00004 (0.001)
TREATMENT	0.695 (0.746)
d2011	0.905 (0.568)
baseline_heduc	0.123*** (0.035)
MA	-4.231*** (0.962)
FV	-2.620* (1.380)
JA	-0.775 (1.049)
POP_3	-0.031 (0.023)
income_mean	1.582 (1.070)
dcutoff:TREATMENT	0.001 (0.001)
TREATMENT1:income_mean	-0.818 (0.883)
Constant	0.304 (0.790)
Observations	47
R2	0.627
Adjusted R2	0.510
Residual Std. Error	1.341 (df = 35)
F Statistic	5.360*** (df = 11; 35)

	HEDUC_6
dcutoff	-0.001 (0.001)
TREATMENT	0.164 (1.047)
d2011	1.826** (0.800)
baseline_heduc	0.213*** (0.049)
MA	-4.130*** (1.334)
FV	-2.628 (1.715)
JA	-1.421 (1.473)
POP_6	-0.061** (0.026)
income_mean	1.764 (1.500)
dcutoff:TREATMENT	0.001 (0.002)
TREATMENT1:income_mean	-1.037 (1.240)
Constant	0.831 (1.145)
Observations	47
R2	0.683
Adjusted R2	0.584
Residual Std. Error	1.882 (df = 35)
F Statistic	6.871*** (df = 11; 35)

	RINCOME_3
dcutoff	-0.004*** (0.001)
TREATMENT	-3.775** (1.553)
d2011	3.431*** (1.227)
baseline_ln_rincome	-1.972 (1.985)
MA	3.717** (1.810)
FV	5.485** (2.383)
JA	0.069 (2.218)
dcutoff:TREATMENT	0.002 (0.002)
Constant	26.039 (20.416)
Observations	47
R2	0.358
Adjusted R2	0.223
Residual Std. Error	2.947 (df = 38)
F Statistic	2.646** (df = 8; 38)

Note: *p<0.1; **p<0.05; ***p<0.01

	RINCOME_6
dcutoff	-0.008***
	(0.002)
TREATMENT	-7.769***
	(2.717)
d2011	7.240***
	(2.146)
baseline_ln_rincome	-5.952*
	(3.473)
MA	2.115
	(3.167)
FV	-1.105
	(4.169)
JA	2.174
	(3.881)
dcutoff:TREATMENT	0.005
	(0.004)
Constant	83.773**
	(35.719)
Observations	47
R2	0.535
Adjusted R2	0.437
Residual Std. Error	5.155 (df = 38)
F Statistic	5.458*** (df = 8; 38)

	RPRICE_3
dcutoff	-0.004
	(0.003)
TREATMENT	-5.078
	(3.465)
d2011	-0.128
	(2.718)
baseline_ln_rprice	16.795***
	(6.066)
MA	30.720***
	(3.849)
FV	42.545***
	(5.003)
JA	3.944
	(4.555)
income_mean	3.542
	(4.300)
dcutoff:TREATMENT	-0.001
	(0.006)
TREATMENT1:income_mean	-0.741
	(4.078)
Constant	-149.628***
	(46.968)
Observations	43
R2	0.918
Adjusted R2	0.892
Residual Std. Error	5.907 (df = 32)
F Statistic	35.847*** (df = 10; 32)

	RPRICE_6
dcutoff	-0.010**
	(0.004)
TREATMENT	-16.379***
	(5.420)
d2011	0.833
	(4.149)
baseline_ln_rprice	47.859***
	(9.328)
MA	25.940***
	(5.861)
FV	38.702***
	(7.644)
JA	8.377
	(9.963)
income_mean	-10.345
	(6.650)
dcutoff:TREATMENT	-0.003
	(0.009)
TREATMENT1:income_mean	2.419
	(6.290)
Constant	-364.005***
	(72.156)
Observations	42
R2	0.838
Adjusted R2	0.786
Residual Std. Error	8.995 (df = 31)
F Statistic	16.043*** (df = 10; 31)

Table 17. Regression estimates for all the variables of interest

Note: *p<0.1; **p<0.05; ***p<0.01

Source: own elaboration with data from Madrid City Council