Assessing Green Gentrification

The Impacts of the New York City Green Infrastructure Project on Property and Rent Values in Kings and Queens

by

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Abstract

Recent studies on the effects of green infrastructure on property values have led to the development of a 'just green enough' strategy, which involves the promotion of small(er)-scale, scattered and fragmented green infrastructure interventions. This research aims to determine whether green infrastructure implementation according to a 'just green enough' strategy can be associated with increases in real estate prices. The New York City Green Infrastructure Project (NYC GIP) applies such a 'just green enough' strategy and is therefore used as a case for this research. Building on the difference-in-difference (DID) technique by using a DID model with a linear time trend, this qualitative analysis aims to identify possible effects of the NYC GIP on property sales values and median gross rent values between 2007 and 2015 in the counties Kings and Queens. The results from this research indicate that there is a positive effect of the implementation of the NYC GIP on property sales values. It has been more difficult to determine whether there is an effect on median gross rent values as well, partly due to the existence of rent stabilization in New York City. Altogether, this research indicates that green infrastructure implementation according to a 'just green enough' strategy is associated with increases in real estate prices – at least in the case of the NYC GIP. Future research should focus on whether the results and conclusion of this research can be generalized, as well as focus on the socioeconomic and sociodemographic effects of green infrastructure implementation according to a 'just green enough' strategy.

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1. Introduction

Increasing urban populations and growing impacts of climate change increasingly impose various pressures and (policy) challenges on the governance of urban areas (WHO, 2017). The WHO (2017) has warned that living in urban areas can even increase the exposure to certain environmental hazards – such as air pollution, extreme heat, and urban flooding – compared to rural living. Research indicates that green infrastructure can play a pivotal role in mitigating and adapting to these exposures and pressures, in particular because of its ability to moderate the impacts of extreme precipitation and temperature (Foster, Lowe & Winkelman, 2011). Green infrastructure is therefore increasingly recognized, both by governments, institutions, and by the scientific community, as an innovative approach and possible solution to mitigate and adapt to increasing climate change pressures and exposures (Aram et al., 2019; Barbosa et al., 2007; van Leeuwen, Nijkamp & de Noronha Vaz, 2010; Nutsford, Pearson & Kingham, 2013; WHO, 2017; Wolch, Byrne & Newell, 2014).

Research over the past decades has demonstrated that there are (physical) health, social, environmental and economic benefits associated with green infrastructure, and that these benefits, alongside its aesthetic value, have positive effects on prices for real estate (Cho, Poudyal & Roberts, 2008; Jim & Chen, 2006; Kong, Yin & Nakagoshi, 2007; Morancho, 2003; Panduro & Veie, 2013; Wolch et al., 2014). Recent studies, however, have started to emphasize that green infrastructure measures cannot just be inconsiderately implemented by some blueprint, but their design has to be thought through, taking into consideration the context in which it is implemented, so its implementation does not lead to disproportionate increases in property values. These insights have led to the development of a 'just green enough' strategy, which involves the promotion of small(er)-scale, scattered and fragmented green infrastructure interventions, rather than grand, geographically concentrated green projects. Such smaller-scale projects provide a more evenly distributing access to green space, rather than creating a focal point for property development strategies that can lead to disproportionate increases in property values in the surrounding area.

This research aims to contribute to the scientific literature on this relative novel 'just green enough' strategy, and aims to determine whether such a strategy is in line with findings of previous studies on the impact of green infrastructure on property values; *i.e.* whether green infrastructure implementation according to such a 'just green enough' strategy is also associated with increases in property values. The New York City Green Infrastructure Project (NYC GIP) applies such a 'just green enough' strategy and is therefore used as a case. This research builds on the difference-in-difference (DID) technique by using a DID model with a linear time trend to identify the possible effects of the NYC GIP on property sales values and median gross rent values between 2007 and 2015 in the counties Kings and Queens. In line with broader literature on the relation between green spaces and property values, the hypotheses are that *the implementation of green infrastructure of the New York City Green Infrastructure Project has had a positive effect on both property sales values and median gross rent values between 2007 and 2015 in the counties Kings and Queens*. Important to note is that this research aims to identify the possible existence of an effect, and whether this effect is positive or negative; in other words, this research is considered to be a qualitative, rather than a quantitative case study.

The research is organised as follows: section 2 provides the theoretical framework and a review of literature on green infrastructure and its impacts on property values. Section 3 then gives a concise overview of the New York City Green Infrastructure Project, as well as of the research area of the counties Kings and Queens. Hereafter, section 4 describes the methodology and data used for this research, with an emphasis on the used DID model. Section 5 then presents the empirical results of the analysis, after which section 6 discusses these results in relation to the hypotheses. Section 6 furthermore discusses the limitations of this research and provides recommendations for future research. Finally, section 7 summarises the findings of this research and provides a conclusion on whether there is an effect of the New York City Green Infrastructure Project on property sales values and median gross rent values between 2007 and 2015 in the counties Kings and Queens.

2. Theoretical Framework

2.1 The Role of Urban Green Infrastructure

Urbanization in the recent decades has resulted in an increasing proportion of the world's population living in cities – since 2007, more than half of the world's population lives in urban areas, a proportion that is expected to increase to 68% by 2050 (United Nations Department of Economic and Social Affairs, 2018; World Bank, 2018A). In the United States, urban population already makes up more than 82% of the total population (World bank, 2018B). The WHO (2017) has warned that living in urban areas limits the access to nature and can increase exposure to certain environmental hazards, such as air pollution, compared to rural living. It also emphasizes the increasing pressures and (policy) challenges that are imposed on the governance of urban areas by increasing urban populations, limited and diminishing resources, and growing impacts of climate change (WHO, 2017).

The role of urban green spaces and green infrastructure is increasingly being recognized as an innovative approach and possible solution to these increasing pressures, both by governments and institutions, as well as by the scientific community (Aram et al., 2019; Barbosa et al., 2007; van Leeuwen et al., 2010; Nutsford et al., 2013; WHO, 2017; Wolch et al., 2014). The benefits from urban green spaces and green infrastructure go beyond just aesthetic values and range from (physical) health benefits, to social, environmental and economic benefits (Heidt & Neef, 2008; Hunter et al., 2019; Lee & Maheswaran, 2011; Zhang et al., 2012; Zhou & Parves Rana, 2011). In the face of the increasing pressures and challenges that climate change is imposing on urban areas, green infrastructure seems to be able to play a pivotal role in mitigating or adapting to these challenges, generally related to their ability to moderate the impacts of extreme precipitation and temperature (Foster et al., 2011). Gill et al. (2007), in their well-known paper on the conurbation of Greater Manchester, provide evidence of the important role that green infrastructure can play in climate change adaptation. Various green infrastructure measures, varying from green roofs, street trees, public parks and private gardens, provide vital ecosystem services which will be even more vital under the pressures of climate change (Gill et al., 2007; Pataki et al., 2011): the carbon cycle (photosynthesis, respiration and growth); nutrient cycles (*e.g.* nitrogen exchange between soil and atmosphere); and water balance (plant transpiration, interception of rain and runoff). These ecosystem services provide, for example, shading and evapotranspirative cooling, which leads to significant reductions in urban heat island effects (Aram et al., 2019; Del Barrio, 1998; Foster et al., 2011; Gill et al., 2007; Sailor, 2008; Sailor, Hutchinson & Bokovy, 2008; WHO, 2017). Also, green infrastructure and its ecosystem services have the ability to reduce storm-water runoff (Chen & Jim, 2008; Zhang et al., 2012; Zhang et al., 2015). Sanders (1986) has provided evidence that an existing 22% tree canopy cover already reduced potential storm water runoff by 7%, and an increase of tree canopy cover to 29% would reduce runoff by 12%. Moreover, green infrastructure leads to improved water infiltration and storage in the soil, compared to less permeable areas, further reducing storm-water runoff (Gill et al., 2007; Whitford, Ennos & Handley, 2001; Zhang et al., 2012). Reductions in runoff and increases in infiltration capacities reduce the risks of flooding (Kielbaso, 2008), reduce the need for large (combined) sewer pipes (McPherson & Rowntree, 1991), and contribute to groundwater recharge (Bowler et al., 2010; Escobedo, Kroeger & Wagner, 2011; Spronken-Smith & Oke, 1998). Therefore, green infrastructure has the ability to improve management of storm-water runoff, to lower combined storm and sewer overflows and thus to reduce the risk of (urban) flooding (Foster et al., 2011; Schulzke & Stoll, 2008; WHO, 2017). In addition, green infrastructure can improve water quality from ground and surface water by trapping sediment and pollutants from urban (storm-)water runoff (Arendt et al., 1994; Schulzke & Stoll, 2008).

2.2 Green Infrastructure and Property Values

Research over the past decades has demonstrated that the (physical) health, social, environmental and economic benefits associated with green infrastructure, alongside its aesthetic value, are reflected in the prices for real estate (Cho et al., 2008; Jim & Chen, 2006; Kong et al., 2007; Morancho, 2003; Panduro & Veie, 2013; Wolch et al., 2014). Predominantly by using hedonic pricing methods, even though interest in stated preference analyses has increased in the past years, researchers are able to gauge external benefits from green infrastructure to real estate prices (Jim & Chen, 2006; Rouwendal & van der Straaten, 2008). The degree to which urban green infrastructure contributes to real estate prices seems to be rather context specific, furthermore depending on the type of green infrastructure, its size and quality, its design and degree of fragmentation, species composition and other, more context specific features (Cho et al., 2008; Jim & Chen, 2006; Kong et al., 2007; Morancho, 2003). But even though the extent to which urban green infrastructure contributes to real estate prices varies over context specifics, the direction of this contribution is rather intuitive and undisputed: there is an inverse relationship between real estate prices and its distance from a urban green infrastructure (Cho et al., 2008; Czembrowski & Kronenberg, 2015; Jim & Chen, 2006; Kong et al., 2007; Morancho, 2003; WHO, 2017; Wolch et al., 2014). Already in 1997, Brown & Pollakowski find that green, public open space in Seattle's lakefront communities has a positive effect on housing prices and that the greater this (view on) public open space, the higher the price for houses. Another (extreme) example is the New York City High Line project, in which an old, dilapidated train rails was revitalized by turning it into a public park. Property values in the area around the High Line have increased as far as 103% between 2003 and 2011 (Brisman, 2012; McGeehan, 2011). Research on the effects of green infrastructure on rent values of real estate, on the other hand, is rather scarce. Nevertheless, intuitively, the same inverse relationship is expected, as rent values are, just as sales values of real estate, determined by different amenities, services and external factors (Sirmans, Sirmans & Benjamin, 1989).

In the economic literature, the increased sales and rental values of real state is often seen as a pure economic benefit from green infrastructure. For example Rouwendal & van der Straaten (2008) use the increase in house values to determine the optimal amount of open space in Dutch cities by means of a cost-and-benefit analysis, whereas Jim & Chen (2006) emphasize the implications of their findings for property developers, focussed around land selling and buying, land conversion and property development. However, various studies, for example Barbosa et al. (2007), Dai (2011) and Wolch et al. (2014) find evidence that spatially access to urban green infrastructure is not evenly distributed across different socioeconomic groups and communities, meaning that the benefits of green infrastructure are also not equally spatially distributed. This has led to the availability of urban green space being also seen a social and environmental justice issue: in many cities, low-income neighbourhoods and marginalized social groups – places and groups for which public health challenges tend to be the most critical – often have relatively poor access to various urban green spaces (Dai, 2011; Wolch et al., 2014).

As a result, there is an increasing emphasis on providing different social and socioeconomic groups with equal amounts of green infrastructure, so that the benefits of this green infrastructure are also equally distributed (Kabisch & Haase, 2014). At the same time, recent studies have also identified the possible negative impacts of increased real estate values and subsequent rent values in socioeconomic vulnerable neighbourhoods as a result of short-sighted implementation of green infrastructure: when not thought through, the implementation of green infrastructure can lead to displacements of residents, as they face higher rent values and are not able to afford increased costs of housing (Anguelovski et al., 2018; Wolch et al., 2014). In other words, the physical gentrification of neighbourhoods – by means of implementing green infrastructure, making the neighbourhood more liveable and attractive – can lead to social gentrification by altering the housing opportunities for socioeconomic vulnerable, often lower income communities in these neighbourhoods (Anguelovski et al., 2018; Wolch et al., 2014; Zukin et al., 2009).

These insights have led to an increasing emphasis on the design and implementation of green infrastructure to better fit the needs of those for whom it is meant, resulting in the development of a 'just green enough' strategy (Curran & Hamilton, 2012; Wolch et al., 2014). 'Just green enough' emphasizes on equal access to (the benefits of) green infrastructure, whilst explicitly addressing the concerns, needs, and desires of the communities in which they are implemented (Heynen et al., 2006; Wolch et al., 2014). It recognizes that green infrastructure measures cannot just be implemented by some blueprint, but their design has to be thought through, taking into consideration the context in which it is implemented and for whom it is meant, so its implementation does disproportionally increase property values (Wolch et al., 2014). This often involves the promotion of small(er)-scale, scattered and fragmented green infrastructure interventions, rather than grand, geographically concentrated green projects (Newman, 2011). Such smaller-scale projects provide a more evenly distributing access to green space, rather than creating a focal point for property development strategies that can lead to disproportionate increases in property values in the surrounding area (Schauman & Salisburry, 1998). The New York City Green Infrastructure Project applies such a 'just green enough' strategy and consists of small(er)-scale, fragmented green infrastructure interventions that are scattered throughout the city.

3. The New York City Green Infrastructure Project

3.1 Policy Overview

The in 2010 released the New York City Green Infrastructure Project (NYC GIP) is part of the larger "PlaNYC: A Greener, Greater New York" – a strategy released in 2007 by Major Bloomberg to prepare the city for various challenges for the coming two decades and to enhance the quality of life for all the residents of New York City, all whilst taking into account the increasing pressures and challenges of global climate change (Bloomberg, 2007). An important part of PlaNYC is cleaning up New York City's rivers, creeks, and coastal waters (Bloomberg & Holloway, 2010). The city waters are polluted by different sources, most notably by combined sewer overflows (CSO): during heavy rainstorms, volume of stormwater runoff overwhelms the combined sewer system, so that treatment plants are unable to handle the amount of runoff. When this occurs, a mixture of untreated sewage and stormwater is discharged directly into the city's waterways, affecting the water quality of these waterbodies and tributaries (Bloomberg & Holloway, 2010; NYC DEP, n.d. A). Next to aesthetic and recreational impacts, CSOs can have severe health impacts for both the residents surrounding the outfall areas, as well as for animal life. Figure 1 gives a visual representation of a CSO.

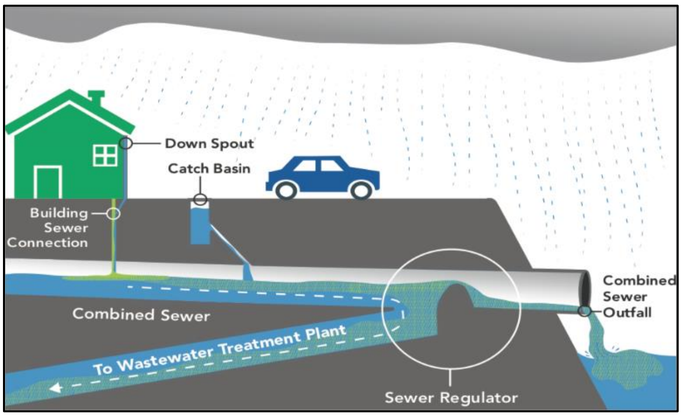


Figure 1. Visual representation of a CSO for a combined sewer system (NYC Environmental Protection, n.d. A).

The NYC GIP aims to reduce these combined sewer overflows by reducing the volume of stormwater runoff by means of green infrastructure measures. The NYC GIP was announced in 2010, and, over a 20-year investment period, the New York City government is willing to spend $1.5 billion in public funds to implement green infrastructure. Moreover, over the same investment period, an added $0.9 billion from private investments in green infrastructure is expected as well. A critical goal is to manage runoff from 10% of the impervious surfaces in combined sewer watersheds through detention and infiltration by green infrastructure measures in order to better manage stormwater runoff and reduce combined sewer overflows by 1.67

billion gallons/year (Bloomberg & Holloway, 2010; NYC DEP, 2018). The NYC Department of Environmental Protection (DEP) has proposed to meet this goal of managing 10% of the impervious surfaces in combined sewer watersheds by achieving 1.5% by 2015, another 2.5% by 2020, another 3% by 2025 and the remaining 3% by 2030 (Bloomberg & Holloway, 2010).

Green infrastructure covers various types of measures, all to be built on public property[1] – *e.g.* sidewalks, streets, and public buildings: (1) rain gardens; (2) stormwater greenstreets; (3) green roofs; (4) blue roofs; (5) permeable paving; (6) subsurface detention systems; and (7) rainbarrels and cisterns (Bloomberg & Holloway, 2010; NYC DEP, n.d. B). The first three of these types of measures include actual vegetated areas, whereas the other four types are labelled as 'green' because of their detaining capacities and permeable characteristics that lead to better management of stormwater at its source (NYC DEP, n.d. B). Pictures and descriptions of each of these measures is provided in Appendix I. It is expected that the implementation strategy of only these green infrastructure measures reduces CSOs by approximately 1.5 billion gallons/year (Bloomberg & Holloway, 2010).

The NYC GIP also emphasizes the cost-effectiveness of green infrastructure compared to the traditional grey measures (*e.g.* tanks and tunnels, which are only useful when it actually rains): it is estimated that the implementation of green infrastructure under the NYC GIP costs $1.5 billion, which is $2.4 billion less than the $3.9 billion needed for additional grey investments to reach the same goal, and leads to an additional 2 billion gallons/year reduction of CSOs (Bloomberg & Holloway, 2010). The NYC GIP does not, however, solely comprise of green infrastructure, but is complemented with an $2.9 billion to spend on cost-effective grey measures to reduce stormwater runoff (Bloomberg & Holloway, 2010). Taking into account these cost-effective grey measures as well, the NYC GIP costs $1.5 billion less than an alternative all-Grey Strategy (Bloomberg & Holloway, 2010).

Even though the main motivation and goal of the NYC GIP is to reduce combined sewer overflows and improve water quality throughout the city, it also contributes to the implementation and objectives of PlaNYC and other 'green' policies introduced by the City government by "[…] *providing substantial, quantifiable sustainability benefits – cooling the city, reducing energy use, increasing property values, and cleaning the air – that the current all Grey Strategy does not provide*." (Bloomberg & Holloway, 2010, p. 3). It is estimated that after the 20-year investment period, these sustainability benefits produce between $139 million and $418 million through reduced energy bills, increased property values, and improved health (Bloomberg & Holloway, 2010).

[1] By the Department of Environmental Protection and the NYC government itself. There are several grant programs and financial tools in place to implement green infrastructure measures on private property (Bloomberg & Holloway, 2010).

After several pilot projects, area-wide green infrastructure projects were launched in 2012, predominantly through the installation of rain gardens (NYC DEP, 2018). As of 2018, all of the area-wide projects in so-called 'Priority CSO Watersheds' are either constructed, in construction, or in advanced design phases, most notably in 'Jamaica Bay' and 'Newton Creek' (NYC DEP, 2018). The first 'milestone' of managing 1.5% of the impervious surfaces in combined sewer watersheds by 2015, however, has not been reached in time (de Blasio & Lloyd, 2015). The next update on the actual progress of the Green Infrastructure Plan in terms of achieving its goal is expected in 2020/2021.

3.2 Kings and Queens Counties

The scope of this research consists of the New York counties Kings and Queens, the first corresponding with the borough of Brooklyn, the second with the eponymous borough of Queens.

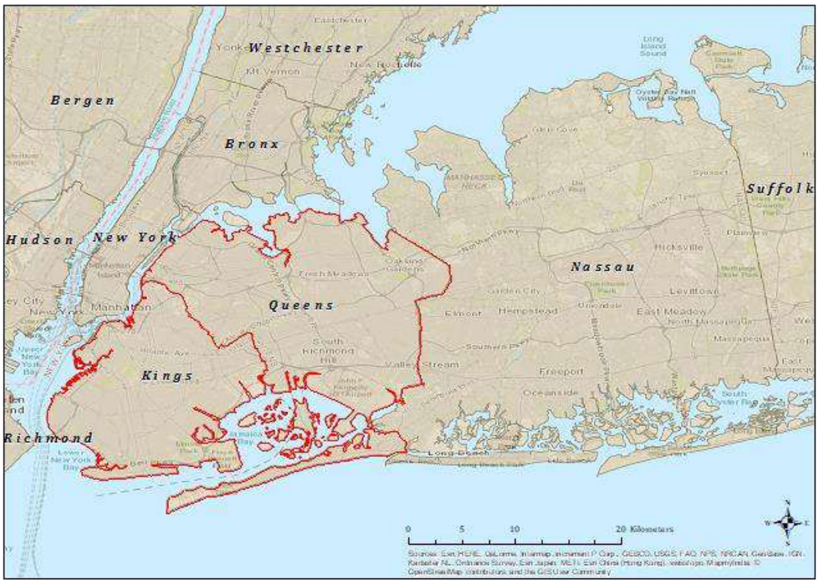


Figure 2. Kings and Queens counties within New York City (Esri, 2019).

Kings and Queens counties have the largest and second-largest populations among the New York City counties, with estimates of more than 2.5 million and 2.3 million residents respectively, together housing more than half of the New York City's population (U.S. Census Bureau, 2018). In terms of housing units, Kings and Queens county have the largest and third-largest amount, containing more than 1 million and 865 thousand housing units respectively in 2018 (U.S. Census Bureau, 2018), of which more than 90% are occupied (969,317 in Kings and 788,100 in Queens) (U.S. Census Bureau, 2019). The rate of these housing units being owner-occupied is 30% for housing units in Kings and 44.6% for housing units in Queens – calculated over the time period 2014-2018 (U.S. Census Bureau, 2018). In other words, renter-occupied housing units makeup most of the housing stock in both counties. It is therefore that this analysis does not focus solely on property values, but also deems it relevant to incorporate rent values.

3.2.1 Relevance of Kings and Queens Counties

As already mentioned, as of 2018, all of the area-wide projects of the NYC GIP in so-called 'Priority CSO Watersheds' are either constructed, in construction, or in advanced design phases, most notably in 'Jamaica Bay' and 'Newton Creek'. The Department of Environmental Protection has identified seven Priority CSO Watersheds based on criteria as the annual CSO volume, frequency of CSO events, system improvements in the future, and the proximity of the CSO outfall to existing and future public access locations (de Blasio & Lloyd, 2013). Of these seven priority CSO Watersheds, five are located within Kings and Queens counties: Jamaica Bay; Newton Creek; Flushing Bay; Flushing Creek; and Gowanus Canal (see: Appendix II). Figure 4 (see: page 17) gives a visual overview of the locations of green infrastructure projects throughout New York City and shows that, indeed, most green infrastructure projects, both finished and planned, are located within the counties of Kings and Queens.

Also the high vulnerability of Kings and Queens to heat related issues has further contributed to green infrastructure measures being implemented within these two counties, because of their ability to lead to significant reductions in urban heat and the urban heat island effects (Bautista et al., 2018; de Blasio & Shorris, 2017; Bloomberg & Holloway, 2010; Foster et al., 2019). Because most of the green infrastructure projects will be implemented first (or have already been implemented) in Kings and Queens, these counties are most relevant to use for this analysis.

4. Methodology

In order to study the effects of the New York City Green Infrastructure Project on property sales values and median gross rent values, this research makes use of an extended DID model that allows for different linear trends between the treatment and control group – both in the pre- and post-treatment period. After providing a detailed explanation of this model and the interpretation of its results, the scope and scale of this research are described, along with the different types and sources of data that have been used for the model.

4.1 The Difference-in-Differences (DID) Model

The 'difference-in-differences' (DID) technique has been pioneered by physician John Snow (1855), who wanted to prove that the cholera outbreaks in London in the mid-nineteenth century were due to contaminated drinking water (Angrist & Pischke, 2008). He compared the changes in death rates from cholera over time between districts serviced by two different water companies: the Southwark and Vauxhall Company and the Lambeth Company – both of which obtained their water supply from the dirty Thames in 1849, whereas the Lambeth Company changed their source of water supply in 1852 upriver to a relatively cleaner area (Angrist & Pischke, 2008). He was able to demonstrate that from 1852, the cholera death rates fell sharply in the districts serviced by the Lambeth Company, compared to the change in death rates in districts served by the Southwark and Vauxhall Company (Angrist & Pischke, 2008). With his design, John Snow laid the foundation of one of the most important identification techniques in empirical economic research and econometrics today (Abadie, 2010; Angrist & Krueger, 1999; Athey & Imbens, 2006; Bertrand, Duflo & Mullainathan, 2004; Card & Krueger, 1994; Heckman, LaLonde & Smith, 1999; Meyer, 1995).

The difference-in-differences technique tries to mimic a natural experiment research design by studying the differential effect of a treatment on an outcome variable of interest (*e.g.* property sales values or median gross rent values) between a 'treatment group' versus a 'control group' (Angrist & Pischke, 2008). Ideally, entities within and between the two groups are identical, except for the fact that the people and locations in the treatment group are exposed to the treatment, whereas those in the control group are not (DiNardo, 2008; Dunning, 2012; Saeed et al., 2019). In economics and social sciences, this treatment is often the implementation of a certain policy or intervention (Abadie, 2010). By comparing the average change over time in the outcome variable of interest between the treatment group and the control group, both pre- and post-treatment, the DID technique calculates the average effect of the treatment (Abadie, 2010; Angrist & Pischke, 2008; Saeed et al., 2019). In order to do so, the DID technique requires data from both the treatment group and the control group from at least one time period before the treatment and one time period after the treatment (*i.e.* panel data) (Abadie, 2010; Angrist & Pischke, 2008; Card & Krueger, 1994).

A basic DID model includes three main variables: an indicator variable for exposure to the treatment (treatment group = 1, control group = 0), an indicator variable for treatment time, whether pre- or post-treatment (pre = 0, post = 1), and the DID estimator, which is the interaction between the treatment and the post-indicator (Saeed et al., 2019):

$$Y = \beta_0 + \beta_1(treatment) + \beta_2(post) + \beta_3(treatment * post) + \epsilon$$

In this linear model, β_0 represents the prevalence of the outcome variable of interest for the control group before the treatment ($treatment = 0$; $post = 0$; $treatment * post = 0$); β_1 describes the time-invariant difference between the treatment group and the control group before the treatment ($treatment = 1$; $post = 0$; $treatment * post = 0$), β_2 represents the secular trend for the control group after the treatment, *i.e.* the difference in the outcome variable of interest compared to pre-treatment in the control group ($treatment = 0$; $post = 1$; $treatment * post = 0$), and β_3, the DID estimator, describes the difference in the outcome variable of interest pre- and post-treatment for the treatment group, *i.e.* the effect of the treatment on the treatment group ($treatment = 1$; $post = 1$; $treatment * post = 1$) (Abadie, 2010; Angrist & Pischke, 2008; Saeed et al., 2019). This DID estimator is thus a double difference between pre- and post-treatment and between the treatment group and the control group (Saeed et al., 2019). Figure 3 presents a visual representation of a basic DID regression model.

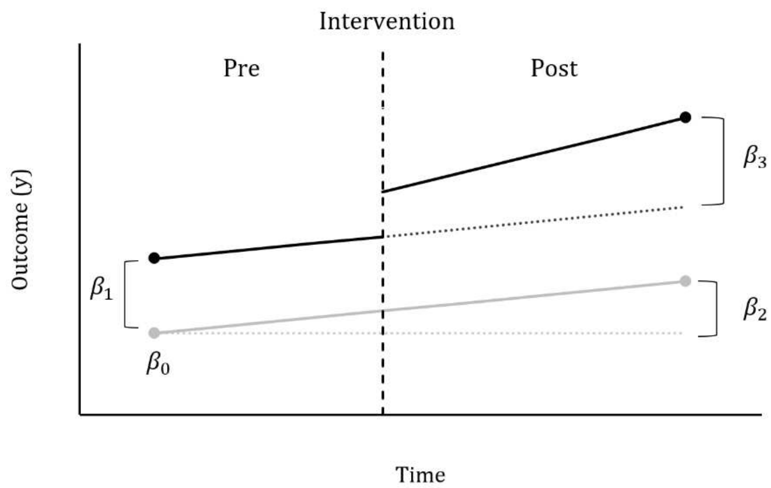


Figure 3. Visual representation of a difference-in-differences design

So, in order to make use of the DID regression model, the distinction between the treatment group and the control group ($treatment$) has to be made explicit, as has the treatment time. For this analysis, the treatment group ($treatment = 1$) is every census tract within the research area that contains at least one constructed green infrastructure project within its boundaries, whereas the control group ($treatment = 0$) consists of the census tracts within the research area that do not contain such a project.[2] The treatment time, on the other hand, has been arbitrarily determined to be a treatment period over multiple years: from 2010 until 2013. To correct for this, another indicator variable is added to the DID model ($during$). This variable indicates whether an observation lies within the treatment period ($= 1$) or not ($= 0$). The indicator variable $post$ still indicates whether an observation lies in either the pre- ($= 0$) or post-treatment period ($= 1$). The basic DID model for this analysis then becomes:

$$Y = \beta_0 + \beta_1(treatment) + \beta_2(post) + \beta_3(treatment * post) + \beta_4(during) + \epsilon$$

Compared to the previous model, the interpretations of β_0, β_1, β_2 and β_3 remain unchanged. β_4 represents the difference in the outcome variable of interest in the treatment period, compared to pre- and post-treatment for both the treatment and control group (depending whether $treatment = 1$ or $= 0$ for a given observation). The development of property sales values and median gross rent values during the treatment period will not be discussed in the analysis. Hence, the interpretation of this coefficient will not be used for the analysis of the results, but merely corrects for the use of a treatment period, rather than a single treatment year.

4.2 The Difference-in-Differences (DID) Model with Linear Time Trend

DID models are based upon the 'parallel trend assumption', meaning that it is assumed that, as in Figure 3, the pre-treatment trends of both the treatment group and the control group are identical (Saeed et al., 2019). This assumption implies that in the absence of treatment, the trends of the outcome variable of interest for both the treatment group and the control group are equal between both the pre- and post-treatment period, *i.e.* assuming a counterfactual trend (Abadie, 2010; Angrist & Pischke, 2008; Card & Krueger, 1994; Saeed et al., 2019). If this assumption holds, β_3 then estimates an unbiased effect of the treatment (Little & Rubin, 2000; Saeed et al., 2019).

However, in reality, this parallel trend assumption is often violated, resulting in either an over- or underestimation of the treatment effect (β_3) (Saeed et al., 2019). Different regression-based approaches, as well as basic visual inspection of the data, can be used to test for parallel trends between the treatment group and control group in the pre-treatment period. Drawing on Angrist & Pischke (2008), Hansen, Sabia & Rees (2017), and Wing, Simon & Bello-Gomez (2018), this research test for parallel trends, as well as corrects for a possible violation of this assumption.

[2] In order to correct for this arbitrary determination of the treatment group, this research includes a sensitivity analysis as well, in which the treatment group is expanded. Section 5.3 provides more information on this.

By adding an indicator variable for time ($2007 = 1, 2008 = 2, \ldots 2015 = 9$) and interacting this indicator variable with the indicator variables for treatment ($treatment$), treatment time ($post$), the DID estimator ($treatment * post$), and treatment period ($during$), the DID regression model takes into account different linear trends between the treatment and control group – both in the pre- and post-treatment period – and tries to estimate the treatment effect more accurately:

$$Y = \beta_0 + \beta_1\,(treatment) + \beta_2\,(post) + \beta_3\,(treatment * post) + \beta_4\,(during) + \beta_5\,(trend) + \beta_6\,(trend * treatment) + \beta_7\,(trend * post) + \beta_8\,(trend * treatment * post) + \beta_9\,(trend * during) + \epsilon$$

In this model, the interpretations of β_0, β_1, β_2, β_3 and β_4 remain the same. The variable $trend$ represents the indicator variable for time. Hence, β_5 represents the effect of time, *i.e.* a linear yearly time trend. β_6 describes the difference in the linear time trend between the treatment group and the control group. β_7 also describes the difference in the linear time trend, but between pre- and post-treatment period for the control group. β_8 represents the relative difference in the linear time trend between the treatment group and the control group in the post-treatment period, compared to the pre-treatment period. β_9 in turn describes the difference in the linear time trend between the treatment period, compared to both the pre- and post-treatment period, for both the treatment and control group (again, depending on whether $treatment = 1$ or $treament = 0$ for a given observation). Also the interpretation of this coefficient will not be used for the analysis of the results; it is merely included to correct for the use of a treatment period, rather than a single treatment year. Altogether, rewriting the DID regression model will then yield the following matrix:

Table 1. Interpretation of coefficients for the indicator variables treatment and post.

	$\boldsymbol{treatment = 0}$	$\boldsymbol{treatment = 1}$
$\boldsymbol{post = 0}$	$\beta_0 + (\beta_5) * trend$	$\beta_0 + \beta_1 + (\beta_5 + \beta_6) * trend$
$\boldsymbol{post = 1}$	$\beta_0 + \beta_2 + (\beta_5 + \beta_7) * trend$	$\beta_0 + \beta_1 + \beta_2 + \beta_3 + (\beta_5 + \beta_6 + \beta_7 + \beta_8) * trend$

The results of this DID regression model will be used to estimate four differences in the in effects on level and trend of the outcome variables for this research, *i.e.* property sales values and median gross rent values:

(1) the difference in the effect on the level of the outcome variable between the pre- and post-treatment period for the treatment group ($\beta_2 + \beta_3$);
(2) The difference in the effect on the level of the outcome variable between the pre- and post-treatment period for the treatment group, relative to the control group (β_3);
(3) the difference in the trend of the outcome variable between the pre- and post-treatment period for the treatment group ($\beta_7 + \beta_8$);
(4) the difference in the trend of the outcome variable between the pre- and post-treatment period for the treatment group, relative to the control group (β_8).

Taking together the results of these four differences, this research then estimates the two differences in level of the outcome variables for this research – with (6) being the 'difference-in-difference' – in order to identify the effects of the New York City Green Infrastructure Project on the outcome variables:

(5) the difference in the level of the outcome variable between the pre- and post-treatment period for the treatment group ($\beta_2 + \beta_3 + (\beta_7 + \beta_8) * trend_{2013} + (\beta_5 + \beta_6) * (trend_{2013} - trend_{2010})$);
(6) the difference in the level of the outcome variable between the pre- and post-treatment period for the treatment group, relative to the control group ($\beta_3 + \beta_8 * trend_{2013} - \beta_6 * (trend_{2013} - trend_{2010})$).

4.3 Data

The scope of this research consists of the New York counties Kings and Queens, the first corresponding with the better-known borough of Brooklyn, over a nine-year period (from 2007 to 2015). Therefore, data used for this research only covers information on the two counties Kings and Queens from 2007 to 2015. The choice of focussing on Kings and Queens as the scope for this research has been explained in section 3.2.1; in short, most green infrastructure projects, both finished and planned, are located within these two counties. The timescale has been determined based on both data availability and on the necessity to have data from at least one year before and one year after the implementation of the NYC GIP (arbitrarily determined to be 2010-2013) in order to sufficiently make us of the DID technique.

The scale of this research is on census tract level. Census tracts are the second smallest geographical entities on which data is publicly available from the United States Census Bureau (U.S. Census Bureau, 2010). Census tracts are, in general, roughly the size of a neighbourhood, although sizes are not predetermined and differ between individual census tracts (U.S. Department of Commerce, Economics and Statistics Administration, & Bureau of the Census, 1994). Using such a small scale allows for a more accurate analysis of the effects of the NYC GIP on property sales values and median gross rent values, as green infrastructure projects are implemented locally (DEP, 2010). Every census tract has an unique tract code, making it usable for both the statistical analysis by means of the DID regression model, as for spatial analysis (U.S. Department of Commerce, 1994). Even though the census tract are relatively permanent, small changes over time can occur (U.S. Department of Commerce, 1994). This research corrects for these changes over time by using yearly census tract layers for every year from 2007 and 2015 in order to spatial reference property sales values and median gross rent values. These layers, called the TIGER/Line® Shapefiles, are downloaded from the U.S. Census Bureau website (https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html). Extracting the census tracts that are located within the boundaries of the counties Kings and Queens provides the underlying spatial census tract layers for every year from 2007 to 2015 on which the relevant variables can be projected and spatially referenced.

4.3.1 Green Infrastructure Projects

Data on locations of green infrastructure projects from the NYC GIP is provided by the NYC Department of Environmental Protection (DEP) through an interactive map of green infrastructure projects. The DEP distinguishes between '*Constructed*' projects, projects '*In Construction*' and projects in '*Final Design*' (NYCDEP_KarolinaR, 2017). Because the DEP regularly updates this map and its underlying database, changes in the status of projects after 5 October 2019, the date of data download, are not taken into account.

By combining the spatial data of the green infrastructure projects with the census tract layers, those green infrastructure projects that are within the boundaries of the counties Kings and Queens have been selected and given a spatial reference, *i.e.* have been assigned the corresponding census tract code of the census tract in which they are located. Figure 4 provides a visual overview of the locations of the green infrastructure projects in New York City and in the counties Kings and Queens.

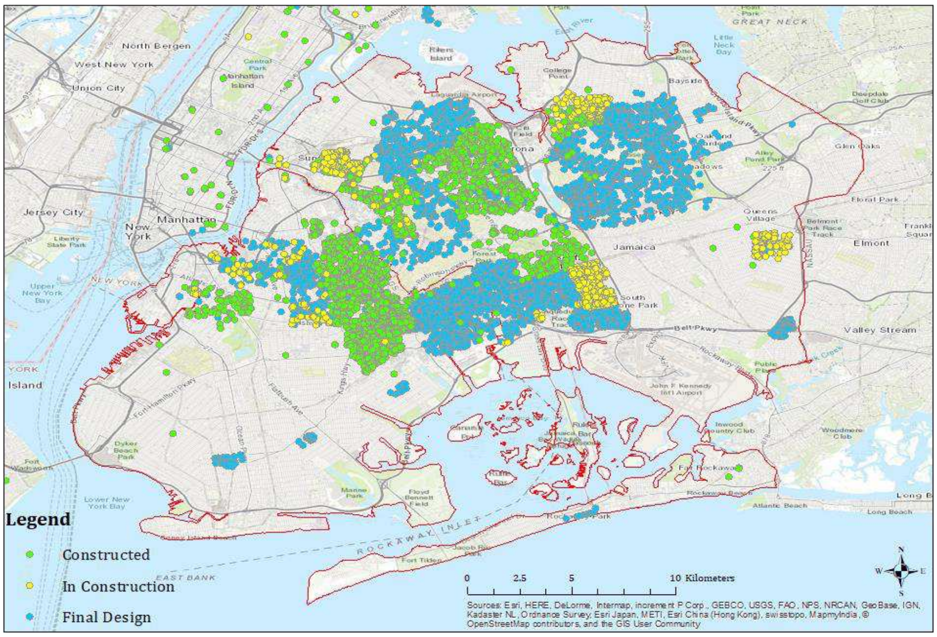
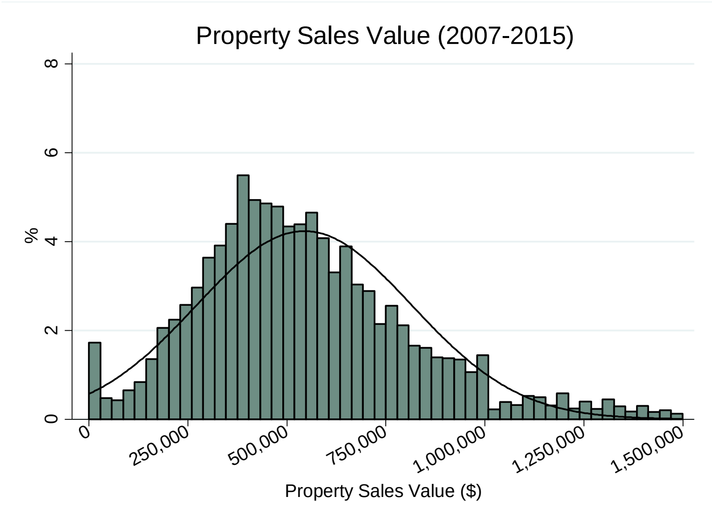


Figure 4. Overview of green infrastructure locations within Kings and Queens counties (NYCDEP_KarolinaR, 2017).

4.3.2 Property Sales Data

New York City's Department of Finance provides Detailed Annual Sales Reports by Borough, which contain data on yearly property sales in New York City – of which the sales price of residential property is the most important for this research. The GIS Lab of The William and Anita Newman Library, part of the Baruch College – The City University of New York, has spatially referenced this data in their NYC Geocoded Real Estate Sales Geodatabase, which is publicly available on the website of the New York University (https://geo.nyu.edu/?f%5Bdct_isPartOf_sm%5D%5B%5D=NYC+Geocoded+Real+Estate+Sales) . By downloading this this spatial data on yearly property sales values for the counties Kings and Queens for every year within the time period 2007-2015 and combining each yearly layer with the corresponding census tract layers, property sales values have been assigned the corresponding census tract code of the census tract in which they are located. This makes it possible to determine whether a property is situated within a census tract level with green infrastructure and hence can be assigned to the treatment group.

From this dataset, only residential data is used ($res\_unit > 0$) in order to only include properties designated for residential use. From this data, only data from residential units that have been declared usable for residential use and have a $price > 0$ are used in order to correct for transactions that contain unusable properties (in accordance with New York State Department of Finance's sale usability criteria) and to correct for the documentation of changes in ownership without an actual transaction ($price = 0$). Lastly, from this data, only data with $price <$ \$1,500,000 are used to correct for outliers in the dataset. Prices have been adjusted to inflation, with 2015 as reference year. A summary of statistics of the property sales values per year in the counties Kings and Queens can be found in Appendix III. Graph 1 visualizes the distribution of the property sales data.



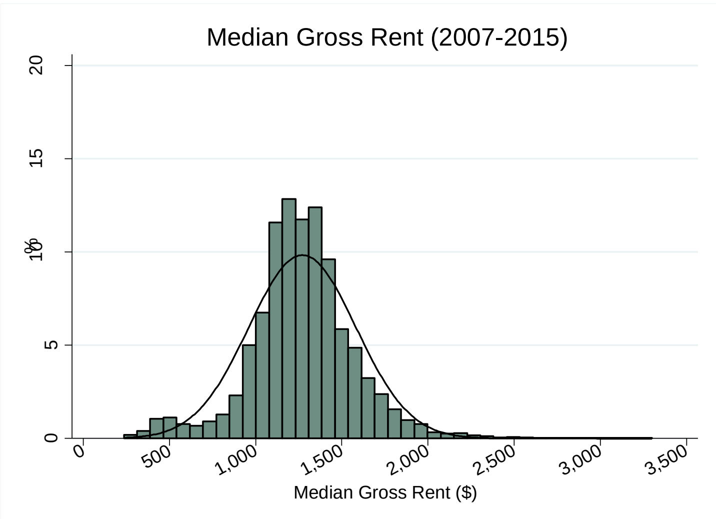
Graph 1. Distribution of property sales values in Kings and Queens (2007-2015).

4.3.3 Median Gross Rent Data

Data on median gross rent values are obtained through the U.S. Census Bureau American Fact Finder (https://factfinder.census.gov/). The U.S. Census Bureau defines 'gross rent' as *"[…] the contract rent plus the estimated average monthly cost of utilities (electricity, gas, and water and sewer) and fuels (oil, coal, kerosene, wood, etc.) if these are paid by the renter (or paid for the renter by someone else)"* (U.S. Census Bureau, 2017, p. 19). This research uses gross rent in order to eliminate differences arising from varying practices with respect to the inclusion of utilities and fuels as part of the rental payment (U.S. Census Bureau, 2017). The median gross rent values represent the divide of the gross rent distribution into two equal parts of a standard distribution: one-half of the cases falling below the median gross rent and one-half above the median (U.S. Census Bureau, 2017).

The U.S. Census Bureau only provides information on median gross rent values on census tract level in so-called 5-year estimates. This means that a median gross rent dataset from a certain year represents also the data from the previous four years: for example, the data in the dataset from 2009 does not actually represent the year 2009, but rather the period 2005-2009. This has an additional benefit of being more reliable than single-year estimates, due to the lower sample variability (U.S. Census Bureau, 2008). However, this also means that, even though the data is more reliable, it is also less current, as the data is also based on the previous four years (U.S. Census Bureau, 2008). Normally one should make a trade-off between the reliability and currency of the census data, but when working with data on census tract level, one cannot work around this due to the way the U.S. Census Bureau obtains and presents its data (U.S. Census Bureau, 2008). Therefore, this research makes the assumption that the average of the 5-year estimate represents this middle year and takes the middle year of the 5-year estimates as a point estimate: *e.g.* the dataset from 2009 represents the period 2005-2009, of which the middle year is 2007. Thus, the 5-year estimate dataset from 2009 is used to represent the estimate for median gross rent values in 2007, the 5-year estimate from 2010 is used to represent the estimate for median gross rent values in 2008, and so forth.

This research focusses on median gross rent values, due to, again, data collection and presentation by the U.S. Census Bureau. The U.S. Census Bureau provides data on gross rent values by categorisation, *i.e.* making arbitrary categories of gross rent values and indicating how many properties fall within each category of gross rent value per census tract. For this research, such categorized data on gross rent values is not usable. More useful is then the median gross rent value for every census tract, also provided by the U.S. Census Bureau. Even though the use of median gross rent values is still far from ideal, it is at least usable for this research. Section 6 will elaborate on the possible effects and implications of using the use of median gross rent data on the results. As mentioned in section 3.2, this research nevertheless includes rent values in its analysis, because more than half of the occupied housing stock in both Kings (70%) and Queens (55%) counties consists of rental property. A summary of statistics of the median gross rent values per year in the counties Kings and Queens can be found in Appendix IV. Graph 2 visualizes the distribution of the property sales data.



Graph 2. Distribution of property sales values in Kings and Queens (2007-2015).

5. Results

This section presents the estimation results of the DID regression model with linear time trend for both property sales values and median gross rent values over the time period 2007-2015 in the counties Kings and Queens. By means of this model, this research aims to determine the effect of green infrastructure projects of the NYC GIP on property sales values and median gross rent values. As mentioned, the results of this DID regression model will be used to estimate four differences in the effects on the level and trend of property sales values and median gross rent values:

(1) the difference in the effect on the level of the outcome variable between the pre- and post-treatment period for the treatment group ($\beta_2 + \beta_3$);
(2) The difference in the effect on the level of the outcome variable between the pre- and post-treatment period for the treatment group, relative to the control group (β_3);
(3) the difference in the trend of the outcome variable between the pre- and post-treatment period for the treatment group ($\beta_7 + \beta_8$);
(4) the difference in the trend of the outcome variable between the pre- and post-treatment period for the treatment group, relative to the control group (β_8).

Taking together the results of these four differences, this section then estimates the two differences in the level of property sales values and median gross rent values – with (6) being the 'difference-in-difference':

(5) the difference in the level of the outcome variable between the pre- and post-treatment period for the treatment group ($\beta_2 + \beta_3 + (\beta_7 + \beta_8) * trend_{2013} + (\beta_5 + \beta_6) * (trend_{2013} - trend_{2010})$);
(6) the difference in the level of the outcome variable between the pre- and post-treatment period for the treatment group, relative to the control group ($\beta_3 + \beta_8 * trend_{2013} - \beta_6 * (trend_{2013} - trend_{2010})$).

In order to estimate these six differences in property sales values and median gross rent values, the estimation results are numerically interpreted by means of Table 1. The findings on changes in property sales values and median gross rent values over the time period 2007-2015 are visually presented as well.

5.1 Property Sales Values

Table 2 (see: next page) shows the estimation results of the DID regression model with linear time trend of the property sales values over the time period 2007-2015 in the counties Kings and

Queens. The estimated coefficients are statistically significant at a 0.1% level, with the exceptions of $Treatment$ (β_1) and $Trend * Treatment$ (β_6), which are significant at a 5% and 1% level respectively.

Table 2. Estimation results of effect green infrastructure on property sales values using panel data.

	Property Sales Values
$Treatment$	-20,428.6*
$Post$	-395,751.1***
$Treatment * Post$	-138,909.2***
$During$	-194,821.7***
$Trend$	-43,535.9***
$Trend * Treatment$	-2,555.7**
$Trend * Post$	88,004.7***
$Trend * Treatment * Post$	23,212.0***
$Trend * During$	56,096.6***
$Constant$	643,265.5***
Observations	196,292
R^2	0.029

Notes: Stars indicate statistical significance. Data cover time period from 2007 to 2015.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

By filing in the estimated coefficients in the equations of Table 1 (p. 14), Table 3 numerically presents the estimation results:

Table 3. Numerical presentation of the estimation results of effect green infrastructure on property sales values using panel data.

	$\boldsymbol{treatment = 0}$	$\boldsymbol{treatment = 1}$
$\boldsymbol{post = 0}$	$643{,}265.5 + (-43{,}535.9) * trend$	$622{,}836.9 + (-46{,}091.6) * trend$
$\boldsymbol{post = 1}$	$247{,}514.4 + (44{,}468.8) * trend$	$88{,}176.6 + (65{,}125.1) * trend$

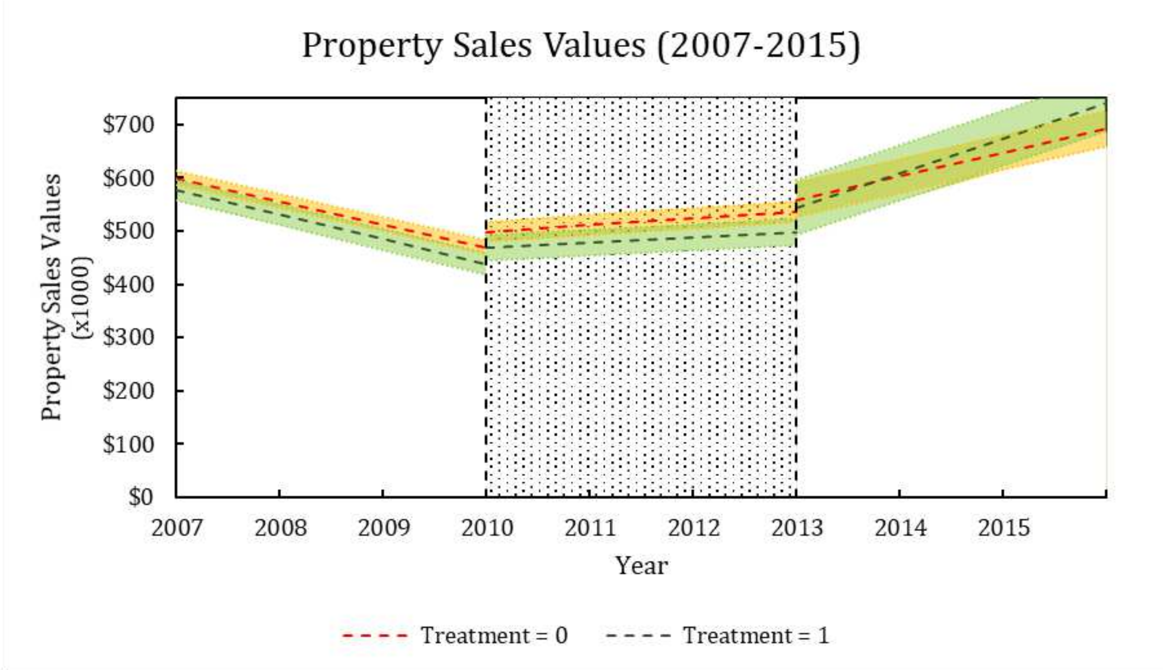
First of all, the estimation results of $Post$ (β_2) and $Trend * Post$ (β_7) indicate that the level of property sales values for the control group is estimated to be \$395,751.10 lower in the post-treatment period than in the pre-treatment period. On the other hand, the yearly trend of property sales values for the control group increases with $88,004.70 in the post-treatment period, relative to the pre-treatment period, and switches from an overall downward trend in the pre-treatment period to an overall upward trend in the post-treatment period – estimated to be $44,468.80 per year. Together with the estimation result of $Trend$ (β_5), these estimation results correspond to a 19.1% higher level of property sales values in the control group at the start of the post-treatment period, compared to at the end of the pre-treatment period.

Second of all, the estimation results of $Post$ (β_2), $Treatment * Post$ (β_3), $Trend * Post$ (β_7), and $Trend * Treatment * Post$ (β_8) represent the differences in the level and trend of property sales values between the pre- and post-treatment period for the treatment group. In the post-treatment period, the level of property sales values for the treatment group is estimated to be $534,660.30 lower than in the pre-treatment period. On the other hand, the yearly trend of property sales values for the treatment group increases with $111,216.70 in the post-treatment period, relative to the trend in the pre-treatment period, and also switches from an overall downward trend in the pre-treatment period to an overall upward trend of $65,125.10 per year in the post-treatment period. Together with the estimation result of $Trend$ (β_5), these estimation results correspond to 24.1% higher property sales values in the treatment group at the start of the post-treatment period, compared to at the end of the pre-treatment period.

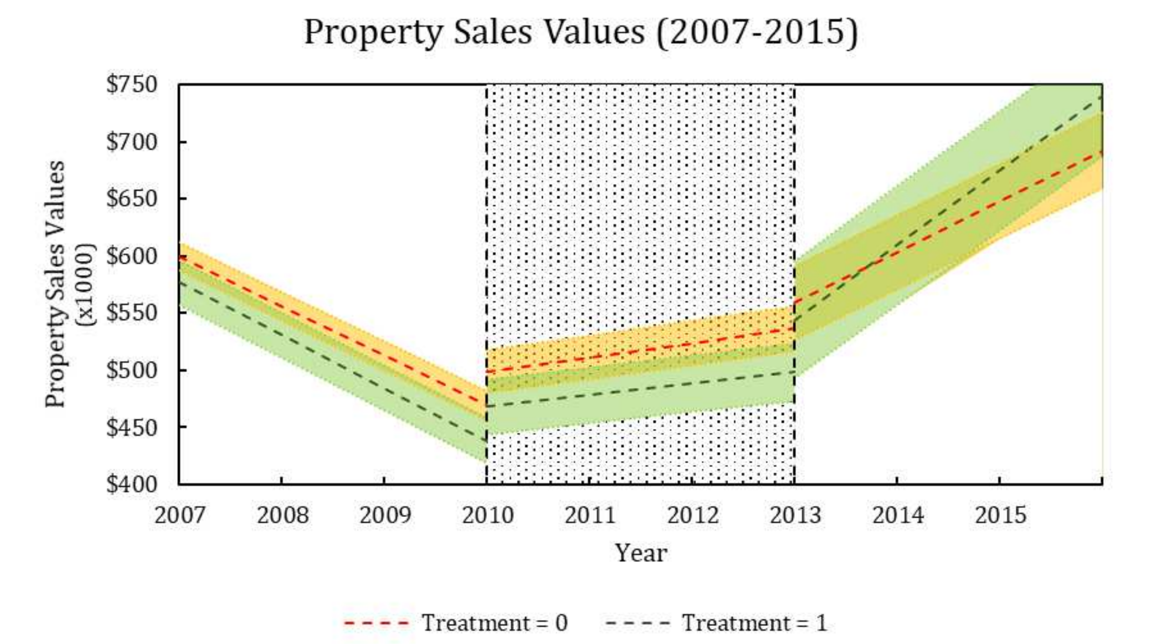
The estimation results of $Treatment$ (β_1) and $Trend * Treatment$ (β_6) indicate that in the pre-treatment period, the level of property sales values in the treatment group is estimated to be $20,428.60 lower than in the control group. The yearly trend of property sales values in the treatment group in the pre-treatment period is estimated to be $2,555.70 lower than the trend of the control group. Together with the estimation result of $Trend$ (β_5), these estimation results correspond to $3.8\% - 6.5\%$ lower property sales values in the treatment group over the course of the pre-treatment period, relative to the control group.

Lastly, the estimation results of $Treatment$ (β_1), $Treatment * Post$ (β_3), $Trend * Treatment$ (β_6), and $Trend * Treatment * Post$ (β_8) represent the difference in level and trend of property sales values between the treatment group and control group in the post-treatment period. In the post-treatment period, the level of property sales values in the treatment group lowers by $159,337.80, relative to the control group. The trend of property sales values in the treatment group, on the other hand, increases with $20,652.30, relative to the control group, to $65,125.10 per year. Together with the estimation result of $Trend$ (β_5), these estimation results correspond to a change in property sales values in the treatment group, relative to the control group, of between -2.6% and $+6.8\%$ over the course of the post-treatment period.

The numerical results from Table 2 and Table 3 can then be used to visualize the estimation results, which gives a more intuitive appeal to the interpretation of the results. Graph 3 visualizes the property sales values over time (2007-2015) for both $treatment = 0$ and $treatment = 1$, including the 95% confidence intervals for the estimation. Graph 4 is the enlarged version of Graph 3, with the vertical axis starting at $400,000 to better visualize the estimation results.



Graph 3. Visual representation of the estimation results of the DID regression model with linear time trend for property sales values (2007-2015).



Graph 4. Visual representation of the estimation results of the DID regression model with linear time trend for property sales values (2007-2015).

From Graph 3 and Graph 4, one can see that the trend in property sales values changes from a downward trend in the pre-treatment period to an upward trend in the post-treatment period. Visually, the differences in level of property sales values between the pre- and post-treatment period are clearly visible as well, both for the treatment group and the control group. Also the significant increase in trend in the post-treatment period for treatment group is visible, with property sales values of the treatment group exceeding those of the control group approximately in 2014.

Altogether, the estimation results of the DID regression model can be used to estimate the six differences in property sales as previously mentioned. Based on the results from Table 2 and Table 3, the numerical interpretation of the coefficients and the visualization of the estimation results, the following conclusions can be drawn:

(1) There is a negative difference in the effect on the level of property sales values between the pre- and post-treatment period for the treatment group: $\beta_2 + \beta_3$, with the negative difference in the effect estimated to be $-\$534,660.30$ in the post-treatment period, relative to the pre-treatment period;
(2) There is a negative difference in the effect on the level of property sales values between the pre- and post-treatment period for the treatment group, relative to the control group: β_3, with the negative difference in the effect estimated to be $-\$138,909.20$, relative to the control group;
(3) There is a positive difference in the trend of property sales values between the pre- and post-treatment period for the treatment group: $\beta_7 + \beta_8$, with the trend of property sales values for the treatment group estimated to be \$111,216.70 higher in the post-treatment period, relative to the pre-treatment period;
(4) There is a positive difference in the trend of property sales values between the pre- and post-treatment period for the treatment group, relative to the control group: β_8, with the trend of property sales values between the pre- and post-treatment period for the treatment group estimated to be \$23,212 higher, relative to the control group.

Taking together the results of these four differences, the two differences in level of property sales values can be estimated – with (6) being the 'difference-in-difference':

(5) There is a positive difference in the level of property sales values between the pre- and post-treatment period for the treatment group: $\beta_2 + \beta_3 + (\beta_7 + \beta_8) * trend_{2013} + (\beta_5 + \beta_6) * (trend_{2013} - trend_{2010})$, with the level of property sales values in the treatment

group estimated to be \$105,581.80 higher (+24.1%) at the start of the post-treatment period, compared to at the end of the pre-treatment period;

(6) There is a positive difference in the level of property sales values between the pre- and post-treatment period for the treatment group, relative to the control group: $\beta_3 + \beta_8 * trend_{2013} + \beta_6 * (trend_{2013} - trend_{2010})$, with the difference in level of property sales values between the pre- and post-treatment period for the treatment group estimated to be \$15,907.70 higher (+17.7%) at the start of the post-treatment period, relative to the control group.

5.2 Median Gross Rent Values

Table 4 shows the estimation results of the DID regression model with linear time trend of the median gross rent values over the time period 2007-2015 in the counties Kings and Queens.

Table 4. Estimation results of effect green infrastructure on median gross rent values using panel data.

	Median Gross Rent
$Treatment$	-19.58
$Post$	-40.64
$Treatment * Post$	5.43
$During$	37.07*
$Trend$	47.12***
$Trend * Treatment$	2.47
$Trend * Post$	-0.39
$Trend * Treatment * Post$	-2.43
$Trend * During$	-10.94**
$Constant$	1,069 ***
Observations	12,287
R^2	0.116

Notes: Stars indicate statistical significance. Data cover time period from 2007 to 2015.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

By filing in the estimated coefficients in the equations of Table 1 (p. 14), Table 5 (see: next page) numerically presents the estimation results:

Table 5. Numerical presentation of the estimation results of effect green infrastructure on median gross rent values using panel data.

	$\boldsymbol{treatment = 0}$	$\boldsymbol{treatment = 1}$
$\boldsymbol{post = 0}$	$1{,}069 + (47.12) * trend$	$1{,}049.42 + (49.59) * trend$
$\boldsymbol{post = 1}$	$1{,}028.36 + (46.73) * trend$	$1{,}014.21 + (46.78) * trend$

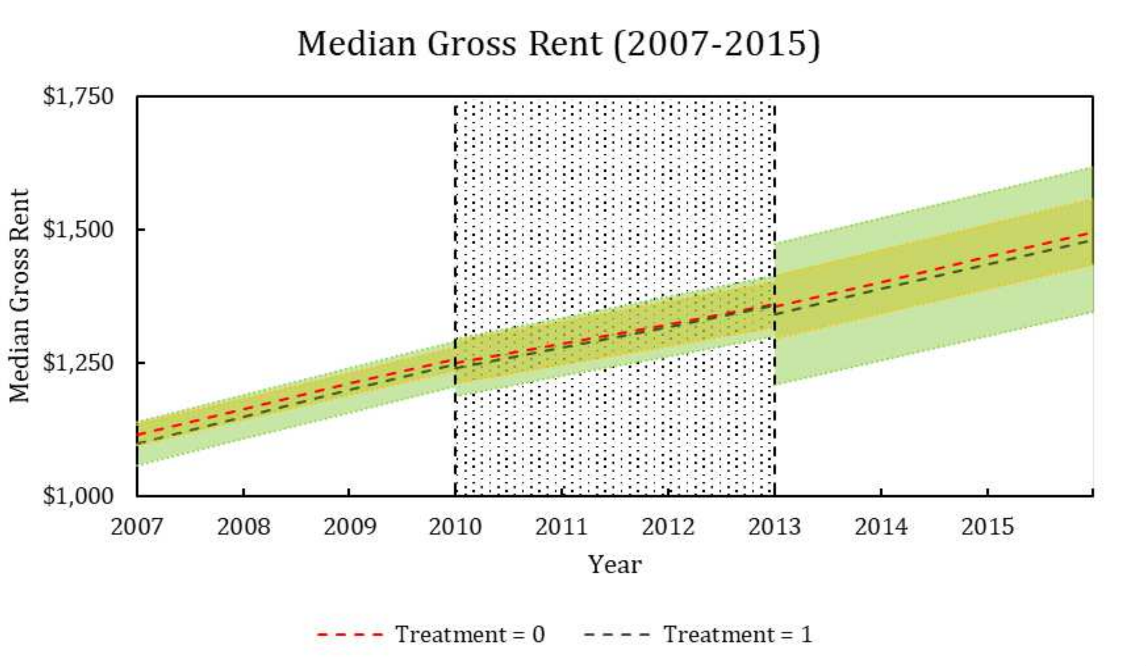
First of all, the estimation results of $Post$ (β_2) and $Trend * Post$ (β_7) indicate that the level of median gross rent values for the control group is estimated to be \$40.64 lower in the post-treatment period than in the pre-treatment period. The yearly trend of median gross rent values for the control group decreases with \$0.39, relative to the pre-treatment period. Together with the estimation result of $Trend$ (β_5), these estimation results nevertheless correspond with a 7.8% higher level of median gross rent values in the control group at the start of the post-treatment period, compared to at the end of the pre-treatment period.

Second of all, the estimation results of $Post$ (β_2), $Treatment * Post$ (β_3), $Trend * Post$ (β_7), and $Trend * Treatment * Post$ (β_8) represent the differences in the level and trend of median gross rent values between the pre- and post-treatment period for the treatment group. In the post-treatment period, the level of median gross rent values for the treatment group is estimated to be \$35.21 lower than in the pre-treatment period. The yearly trend of median gross rent values for the treatment group decreases with \$2.81, relative to the trend in the pre-treatment period, to \$46.78 per year in the post-treatment period. Together with the estimation result of $Trend$ (β_5), these estimation results correspond to 7.5% higher median gross rent values in the treatment group at the start of the post-treatment period, compared to at the end of the pre-treatment period.

The estimation results of $Treatment$ (β_1) and $Trend * Treatment$ (β_6) indicate that in the pre-treatment period, the level of median gross rent values in the treatment group is estimated to be \$19.58 lower than median gross rent values in the control group. On the other hand, the yearly trend of median gross rent values in the treatment group is estimated to be \$2.47 higher in the pre-treatment period, relative to the trend of the control group. Together with the estimation result of $Trend$ (β_5), these estimation results correspond to $0.8\% - 1.5\%$ lower median gross rent values in the treatment group in the pre-treatment period, relative to the control group.

Lastly, the estimation results of $Treatment$ (β_1), $Treatment * Post$ (β_3), $Trend * Treatment$ (β_6), and $Trend * Treatment * Post$ (β_8) represent the difference in the level and trend of median gross rent values between the treatment group and control group in the post-treatment period. In the post-treatment period, the level of median gross rent values in the treatment group lowers by \$14.15, relative to the control group. The trend of median gross values in the treatment group increases – be it by only \$0.04 relative to the control group – to \$46.78 per year. Together with the estimation result of $Trend$ (β_5), these estimation results correspond to a decrease in median gross rent values in the treatment group of $0.9\% - 1\%$ in the post-treatment period, relative to the control group.

The numerical results from Table 4 and Table 5 can then be used to visualize the estimation results, which gives a more intuitive appeal to the interpretation of the results. Graph 5 visualizes the median gross rent values over time (2007-2015) for both $treatment = 0$ and $treatment = 1$, including the 95% confidence intervals for the estimation. Note that the vertical axis starts at \$1000 to better visualize the estimation results.



Graph 5. Visual representation of the estimation results of the DID regression model with linear time trend for median gross rent values (2007-2015).

From Graph 5, one cannot see clearly that the trend in median gross rent values in the post-treatment period changes, as these changes in trend for the treatment and control group are relatively small (see: Table 4 or Table 5). The changes in level of median gross rent values in the post-treatment period for the treatment and control group, relative to the pre-treatment period, is better observable. The differences in median gross rent values between the treatment and control group, both in the pre- and post-treatment period, are also visible in Graph 5, albeit relatively small. The upward linear trend in the median gross rent values for both the treatment and control group, both in the pre- and post-treatment period, can also be recognised, which coincides with the interpretation of the estimation results.

Altogether, the estimation results of the DID regression model can be used to estimate the six differences in median gross rent values as previously mentioned. Based on the results from Table 4 and Table 5, the numerical interpretation of the coefficients and the visualization of the estimation results, the following conclusions can be drawn:

(1) There is a negative difference in the effect on the level of median gross rent values between the pre- and post-treatment period for the treatment group: $\beta_2 + \beta_3$, with the negative difference in the effect estimated to be $-\$35.21$ in the post-treatment period, relative to the pre-treatment period;
(2) There is a positive difference in the effect on the level of median gross rent values between the pre- and post-treatment period for the treatment group, relative to the control group: β_3, with the positive difference in the effect estimated to be \$5.43, relative to the control group;
(3) There is a negative difference in the trend of median gross rent values between the pre- and post-treatment period for the treatment group: $\beta_7 + \beta_8$, with the trend of median gross rent values for the treatment group estimated to be $-\$2.82$ lower in the post-treatment period, relative to the pre-treatment period;
(4) There is a negative difference in the trend of median gross rent values between the pre- and post-treatment period for the treatment group, relative to the control group: β_8, with the difference in the trend of median gross rent values between the pre- and post-treatment period for the treatment group estimated to be $-\$2.43$ lower, relative to the control group.

Taking together the results of these four differences into account, the two differences in level of median gross rent values can be estimated – with (6) being the 'difference-in-difference':

(5) There is a positive difference in the level of median gross rent values between the pre- and post-treatment period for the treatment group: $\beta_2 + \beta_3 + (\beta_7 + \beta_8) * trend_{2013} + (\beta_5 + \beta_6) * (trend_{2013} - trend_{2010})$, with the level of median gross rent values in the treatment group estimated to be \$93.82 (+7.5%) higher at the start of the post-treatment period, compared to at the end of the pre-treatment period;
(6) There is a negative difference in the level of median gross rent values between the pre- and post-treatment period for the treatment group, relative to the control group: $\beta_3 + \beta_8 * trend_{2013} + \beta_6 * (trend_{2013} - trend_{2010})$, with the difference in level of median gross

rent values between the pre- and post-treatment period for the treatment group estimated to be $-\$4.17$ lower (-4.2%) at the start of the post-treatment period, relative to the control group.

However, it is important to note that the estimation results in Table 4 are, with the exception of the variables $During$ (β_4), $Trend$ (β_5), and $Trend * During$ (β_9), not statistically significant at at least the 5% level. However, the DID regression model calculates point estimates – single values that serve as a best estimate. Even though some of these estimates are not statistically significant and imply no statistically significant correlation between the implementation of green infrastructure and the increase in median gross rent values, these estimates have, to a certain extent, economic significance and implications, as they contribute to median gross rent values – albeit relatively less. Nevertheless, when interpreting these results, one has to keep in mind that the estimation results cannot be considered statistically significant. Section 6 elaborates more hereon.

5.3 Sensitivity of Results

This section aims to evaluate the sensitivity of the estimation results from sections 5.1 and 5.2, with respect to the arbitrary determination of the treatment group (and consequently the control group). Hence, this sensitivity analysis evaluates how a change in the determination of the treatment and control group can change the estimation results and what the potential implications are for the conclusions drawn in sections 5.1 and 5.2.

As mentioned in section 4.1, the treatment group consists of every census tract within the research area that contains at least one green infrastructure project within its boundaries, whereas the control consists of the census tracts within the research area that do not contain such a project. This sensitivity analysis increases the extent of the treatment group by including every census tract within the research area that has been appointed at least one green infrastructure project within its boundaries (*i.e.* not only '*Constructed*' projects, but projects '*In Construction*' and in '*Final Design*' as well – see: Figure 4). Moreover, census tracts adjacent to those that contains at least one green infrastructure project within its boundaries are also included in the treatment group. All the other census tracts within the research area – *i.e.* those that have not been appointed at least one green infrastructure project within their boundaries and do not border a census tract that has at least one green infrastructure project already constructed within its boundaries – comprise the control group.

Because the DID regression model calculates point estimates – single values that serve as a best estimate – it is to be expected that estimation results differ between the two regressions. Therefore, it is not the fact that there is a difference between the estimation results that is relevant *per se*. What is relevant for this sensitivity analysis are the implications of these differences for the conclusions drawn in sections 5.1 and 5.2. These implications depend partly on the potential changes in direction (*i.e.* from positive to negative or *vice versa*) of the estimated coefficients, as well as changes in the sizes of the estimated coefficients. Therefore, the focus will be on the potential changes in direction, as well as changes in the sizes of the estimated coefficients.

5.3.1 Sensitivity of Results – Property Sales Values

Appendix V provides a visual representation of the estimation results of the regression with the expanded treatment group to enable a visual comparison of this sensitivity analysis.

Table 6. Estimation results of effect green infrastructure on property sales values using panel data.

	(1) Property Sales Values	(2) Property Sales Values
$Treatment$	-20,428.6*	-13,500
$Post$	-395,751.1***	-376,903.9***
$Treatment * Post$	-138,909.2***	-79,628.9***
$During$	-194,821.7***	-194,371.5***
$Trend$	-43,535.9***	-40,477.4***
$Trend * Treatment$	-2,555.7**	-6,021.7***
$Trend * Post$	88,004.7***	83,670.9***
$Trend * Treatment * Post$	23,212***	15,287.3***
$Trend * During$	56,096.6***	56,005.7***
$Constant$	643,265.5***	646,030.4***
Observations	196,292	196,292
R^2	0.029	0.030

Notes: Stars indicate statistical significance. Data cover time period from 2007 to 2015.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6 presents the estimation results of the regression with the expanded treatment group next to the estimation results from section 5.1. It shows, first of all, that there are no differences in terms of direction between the estimation results of both regressions: all estimation results from section 5.1 that are positive (/negative) are also positive (/negative) in the regression with the expanded treatment group. This indicates that a change in the determination of the treatment and control group does not change the estimation results in terms of direction.

Second of all, in terms of size of the estimation results, Table 6 shows that the coefficients of the variables $Treatment$ (β_1), $Treatment * Post$ (β_3), $Trend * Treatment$ (β_6), and $Trend * Treatment * Post$ (β_8) differ considerably between both regressions. Even though these differences in size of the estimation results are considerable, the implications of these differences on the conclusions drawn in sections 5.1 depend on the relative effect of these variables, compared to the other variables – not so much on the change of the size itself. The changes in size do, however, change the actual differences in level and trend of property sales values. Nevertheless, the considerable differences in size of the estimation results do not affect the conclusions drawn in sections 5.1, hence these conclusions still hold:

(1) There is still a negative difference in the effect on the level of property sales values between the pre- and post-treatment period for the treatment group: $\beta_2 + \beta_3 = -\$456,532.80$;
(2) There is still a negative difference in the effect on the level of property sales values between the pre- and post-treatment period for the treatment group, relative to the control group: $\beta_3 = -\$79,628.90$;
(3) There is still a positive difference in the trend of property sales values between the pre- and post-treatment period for the treatment group: $\beta_7 + \beta_8 = \$98,958.20$;
(4) There is still a positive difference in the trend of property sales values between the pre- and post-treatment period for the treatment group, relative to the control group: $\beta_8 = 15,287.30$;
(5) There is still a positive difference in the level of property sales values between the pre- and post-treatment period for the treatment group: $\beta_2 + \beta_3 + (\beta_7 + \beta_8) * trend_{2013} + (\beta_5 + \beta_6) * (trend_{2013} - trend_{2010}) = \$96,677.30$ (+21.6%);
(6) There is still a positive difference in the level of property sales values between the pre- and post-treatment period for the treatment group, relative to the control group: $\beta_3 + \beta_8 * trend_{2013} + \beta_6 * (trend_{2013} - trend_{2010}) = \$9,317.10$ (+10.7%).

It is worth mentioning that in Table 6, the estimation result of the variable $Treatment$ (β_1) of the regression with the expanded treatment group is no longer significant at at least the 5% level. Even though the sensitivity analysis implies no implications on the economic significance of the estimation results, a change in the determination of the treatment and control group does change the statistical significance of the estimation results – that of $Treatment$ (β_1). However, the variable $Treatment$ (β_1) does not influence the conclusions drawn in sections 5.1. Therefore, the change the statistical significance of the estimation results does not affect these conclusions, so that these are still considered to hold when confronted with a change in the determination of the treatment and control group.

5.3.2 Sensitivity of Results – Median Gross Rent Values

Appendix VI provides a visual representation of the estimation results of the regression with the expanded treatment group to enable a visual comparison of this sensitivity analysis.

Table 7. Estimation results of effect green infrastructure on median gross rent values using panel data..

	(1) Median Gross Rent	(2) Median Gross Rent
$Treatment$	-19.58	41.42*
$Post$	-40.64	16.23
$Treatment * Post$	5.43	-58.28
$During$	37.07*	40.08*
$Trend$	47.12***	47.92***
$Trend * Treatment$	2.47	-1.187
$Trend * Post$	-0.39	-9.305
$Trend * Treatment * Post$	-2.43	7.216
$Trend * During$	-10.94**	-10.32*
$Constant$	1,069 ***	1002.6***
Observations	12,287	12,507
R^2	0.116	0.070

Notes: Stars indicate statistical significance. Data cover time period from 2007 to 2015.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7 presents the estimation results of the regression with the expanded treatment group next to the estimation results from section 5.2. It shows, first of all, that there are five differences in terms of direction between the estimation results of both regressions: in the regression with the expanded treatment group, the coefficients of the variables $Treatment$ (β_1), $Post$ (β_2), and $Trend * Treatment * Post$ (β_8) change from negative to positive, whereas the coefficients of the variables $Treatment * Post$ (β_3) and $Trend * Treatment$ (β_6) change from positive to negative. This indicates that a change in the determination of the treatment and control group does change the estimation results in terms of direction. The implications of this will be evaluated further below.

Second of all, in terms of size of the estimation results, Table 7 shows that there are considerable differences between the estimation results of both regressions – which is to be expected, due to the changes in direction of five variables; all of these five variables show considerable changes in the sizes of their respective coefficients. In addition to the coefficients of these five variables, the coefficient of the variable $Trend * Post$ (β_7) shows a change worth mentioning. Again, even though these differences in size of the estimation results are considerable, the implications of these differences on the conclusions drawn in section 5.2 depend on the relative effect of these variables, compared to the other variables. Moreover, the identified differences in direction of the estimation results need to be taken into account as well. Altogether, the considerable differences in size of the estimation results, as well as the changes in direction of the coefficients of five variables, affect the conclusions drawn in section 5.2 the following:

(1) There is still a negative difference in the effect on the level of median gross rent values between the pre- and post-treatment period for the treatment group: $\beta_2 + \beta_3 = -\$42.05$;
(2) There is a change from a positive to a negative difference in the effect on the level of median gross rent values between the pre- and post-treatment period for the treatment group, relative to the control group: $\beta_3 = -\$58.28$, instead of \$5.43;
(3) There is still a negative difference in the trend of median gross rent values between the pre- and post-treatment period for the treatment group: $\beta_7 + \beta_8 = -\$2.01$;
(4) There is a change from a negative to a positive difference in the trend of median gross rent values between the pre- and post-treatment period for the treatment group, relative to the control group: $\beta_8 = 7.22$, instead of $-\$2.43$;
(5) There is still a positive difference in the level of median gross rent values between the pre- and post-treatment period for the treatment group: $\beta_2 + \beta_3 + (\beta_7 + \beta_8) * trend_{2013} + (\beta_5 + \beta_6) * (trend_{2013} - trend_{2010}) = \$83.53\ (+6.8\%)$;
(6) There is still a negative difference in the level of median gross rent values between the pre- and post-treatment period for the treatment group, relative to the control group: $\beta_3 + \beta_8 * trend_{2013} + \beta_6 * (trend_{2013} - trend_{2010}) = -\$11.32\ (-11.9\%)$.

Again, it is important to note that the estimation results in Table 7 are, with the exception of the variables $During$ (β_4), $Trend$ (β_5), and $Trend * During$ (β_9), not statistically significant at at least the 5% level. However, in the regression with the expanded treatment group, the coefficient of the variable $Treatment$ (β_1) becomes statistically significant at at least the 5% level as well. Again, a change in the determination of the treatment and control group does change the statistical significance of the estimation results – that of $Treatment$ (β_1). However, the variable $Treatment$ (β_1) does not influence the conclusions drawn in sections 5.2, nor the changes in conclusions (2) and (4). Therefore, the change the statistical significance of the estimation results does not affect these conclusions drawn in sections 5.2, nor the changes in conclusions (2) and (4).

Even though the determination of the treatment group and control group affects the conclusions (2) and (4) drawn in section 5.2, it does not affect the conclusions (5) and (6), *i.e.* the two differences in level of median gross rent values. It is worth noting that the conclusions (2) and (4) are impacted by a change in the determination of the treatment group and control group, but it will not affect the overall conclusions of this research.

6. Discussion

This section discusses the empirical results from section 5. For both property sales values and median gross rent values, the results are summarized and interpreted. Hereafter, the results are discussed in relation to the possible limitations from the research set-up, used methodology, and used data. This sections concludes with recommendations for future research.

6.1 Discussion of Results

The results on property sales values presented in section 5.1 suggest that there is a positive difference in the level of property sales values, both between the pre- and post-treatment period for the treatment group, as well as when compared to the control group. Even though the sensitivity analysis in section 5.3 indicates a smaller difference, it confirms these results. Also, the results indicate that there is an increase in property sales values in the control group in the post-treatment period, albeit smaller than for the treatment group. This suggests that there might be some spill-over effect from census tracts with implemented green infrastructure to census tracts without. Moreover, these results also show a shift from an overall downward trend for property sales values in the pre-treatment period to an increasing trend in the post-treatment period. More specifically, the property values for the treatment group exceed those from the control group in the post-treatment period, due to the higher yearly trend in property sales values for the treatment group. Altogether, these results indicate that there is indeed a positive effect of the implementation of the New York City Green Infrastructure Project on the property sales values. This is in line with the hypothesis that there is a positive effect of the implementation of green infrastructure on property sales values. This also fits with the findings of previous studies on the effects of green infrastructure on property values (Cho et al., 2008; Jim & Chen, 2006; Kong et al., 2007; Morancho, 2003; Panduro & Veie, 2013; Wolch et al., 2014); that the different benefits associated with green infrastructure, alongside its aesthetic value, are reflected in increased prices for real estate. The results of this study build on this existing evidence of the effects of green infrastructure on property values by indicating that the same impact applies to a 'just green enough' strategy – at least in the case of the New York City Green Infrastructure Project.

The results on median gross rent values presented in section 5.2, on the other hand, suggest that there is a positive difference in level of median gross rent values between pre- and post-treatment period for the treatment group, but when compared to the control group, there is a negative difference in level of median gross rent values between pre- and post-treatment period for the treatment group. The sensitivity analysis in section 5.3 coincides also with these results. Taken together, these results seem to indicate something rather counterintuitive: that there is a negative effect of the implementation of the New York City Green Infrastructure Project on the median gross rent values. This is not in line with the hypothesis, which expected the same relation between green infrastructure and median gross rent values as for property sales values. However, as mentioned in section 5.2, it needs to be taken into account that the estimation results for median gross rent values are not statistically significant at at least the 5% level, with the exception of the variables $During$ (β_4), $Trend$ (β_5), and $Trend * During$ (β_9). There is therefore statistically no significant correlation between the implementation of green infrastructure and median gross rent values.

A rather plausible explanation for this is the existence of rent control programs in New York City – especially the rent stabilization program, which ensures that rents can only increase by certain percentage (NYC Rent Guidelines Board, n.d.). In other words, rent stabilization restricts how much rents in certain residential housing units can increase annually (NYC Furman Center, 2014). The allowed increase in rents does not depend on income level, the apartment size, the amount of people living there, nor any other needs-based factors (Nonko, 2020). In 2011, almost 1 million rental units, approximately 45% of all the rental units in New York City, were rent-stabilized; in Kings and Queens counties, this was 44.3% and 43.3% respectively (NYC Furman Center, 2014). The existence of rent stabilization in New York City seems to prevent the reflection of the impact of the implementation of green infrastructure on rent values, because it restricts the amount of yearly increase in rent. Hence, the existence of rent stabilization can help to explain the estimation results for median gross rent values not being statistically significant at at least the 5% level. It furthermore oppugns the negative effect of the implementation of the New York City Green Infrastructure Project on the median gross rent values, as indicated by the results of section 5.2. Altogether, this makes it difficult to determine whether there is indeed an effect of the implementation of the New York City Green Infrastructure Project on the median gross rent values and whether this effect is positive or negative.

6.2 Limitations

It is important to acknowledge that the set-up of this research, as well as the used methodology and data, have their limitations and constraints on the interpretation and implication of the results. These limitations have to be discussed in order to put the results and their implications in a more nuanced context.

6.2.1 Data on Green Infrastructure Projects

As this research has been highly dependent on the availability and detail of the necessary data, the lack of some specific data has imposed limitations on this research. The data on the green infrastructure measures in particular has put some constraints on this research, as it provided limited to no information as to what type of measure was implemented on what location and when. As mentioned in Chapter 3.1, there are also non-vegetated types of measures implemented as part of the NYC GIP, but the data provided by the NYC Department of Environmental Protection does not allow for differentiating between these types measures, so that also non-vegetated measures had to be taken into account for this analysis. If it were possible to only use data on the vegetated measures, this research would have been able to better identify the effects of actual 'green' infrastructure on property sales values and median rent values. Nevertheless, this research has aimed to identify the effects of the New York City Green Infrastructure Project as a whole, which also includes the possible effects of non-vegetated measures.

The data provided by the NYC Department of Environmental Protection also does not allow for determining when a green infrastructure measure has been fully implemented. This research would have benefited if it were possible to do so, because it enables for a more deliberate choice for a treatment year, based on the relative amount of implemented green infrastructure. This research has tried to overcome this limitation by defining a treatment period, rather than a single treatment year. However, even though the large-scale implementation of green infrastructure measures started within the determined treatment period, the lack of information on when a green infrastructure measure has been fully implemented might have led to the incorporation of census tracts in the treatment group without that census tract having a green infrastructure measure within its boundaries during the treatment period. Nevertheless, the number of census tracts that have possibly been wrongly assigned to the treatment group is rather small – if any – compared to the total number of census tracts. Hence, it is not likely that this has substantially impacted the results of this research.

6.2.2 Data on Median Gross Rent Values

As mentioned in section 4.3.3, due to data collection and presentation by the U.S. Census Bureau, this research has had to use data on median gross rent values on a census tract level, rather than individual rent data. Compared to individual rent values, the median value is rather meaningless in the sense that it does not reflect the effect of different characteristics and factors that determine individual rent values, such as size of the residence or the number of rooms. However, the main limitation that arises from having to use the median value is that, compared to individual rent values, the median value is to a lesser extent able to reflect the effect of green infrastructure on rent values, because this median value is on a census tract level; in other words, the effects of green infrastructure on individual rent values are overshadowed by the aggregation of rent values on a census tract level. Nevertheless, as discussed in section 6.1, the existence of rent stabilization in New York City makes it difficult to determine whether there is an effect of the implementation of green infrastructure on rent values at all. So even if data on individual rent values would have been available for this research, its comparative advantage over the median value would only have made a difference in the estimation results, but it would in all probability not have made an impact on the overall findings and conclusions of this research.

6.2.3 *Limitations of Methodology*

The used methodology of this research, in particular the difference-in-difference model has its limitations on the interpretation and implication of the results as well. Most important to note and acknowledge is that, even though the results in section 5 give a value to the estimated differences, the difference-in-difference model itself does not allow for a quantitative analysis. In other words, the estimation results of the difference-in-difference model can be used to identify the direction of an effect of the implementation of green infrastructure on property sales values and median gross rent values (*i.e.* whether the effect is positive or negative), but the results are not suitable to identify the actual size of the effect. The difference-in-difference model does not take into account different types of residences, nor differences in residence attributes that contribute to its value (*e.g.* the size, the number of rooms, or the construction year of the residence). As such, the difference-in-difference model is also not suitable to do determine the relative effect of green infrastructure on property sales values and median gross rent values. Altogether, the used methodology is qualitative, rather than quantitative, and therefore the results and conclusions of this research can only be interpreted qualitatively; quantitative results are and conclusions are beyond the scope of this research.

Also, the difference-in-difference model cannot not account for other (large) projects in the research area that could have had an impact on property sales values and median gross rent values in their vicinity, for example the construction of a subway tunnel or a large parking lot. Even though this research has not been able to identify projects in the research area between 2007 and 2015, it does not mean that there has not been one. Nevertheless, it is expected that the effects of such projects are overshadowed in the estimation results due to the large research area and hence large sample size of property sales values and median gross rent values. Therefore, it is not expected that the existence of other (large) projects in the research has impacted the results of this research.

Finally, it is important to note the spatial aggregation arisen from the set-up of this research and the used methodology. This research has determined its treatment and control group on a census level, with every census tract within the research area that contains at least one 'constructed' green infrastructure measure within its boundaries being assigned to the treatment group. So, even if there has only been one green infrastructure measures constructed within the boundaries of a census tract, the census tract is assigned to the treatment group. This also implies that, in the case of the property sales data, all the individual property sales values within that census tract are assigned to the treatment group as well – even if a property is not in the vicinity of that green infrastructure measure. This research was not able to overcome such spatial aggregation of data, because the census tract level is the smallest geographical scale on which data for this research has been made publicly available, and on which the difference-in-difference method of this research could be executed. Nevertheless, even though the spatial aggregation is not preferable, it has no impact on the overall conclusion of this research regarding property sales values; if this research were able to not overcome the spatial aggregation of data (*i.e.* only take into account the properties in the vicinity of a green infrastructure measure), the results on property sales values of this analysis would, in all likelihood, only be stronger. In other words, the effect of the implementation of green infrastructure measures on property sales values would then be higher – but the direction of the effect would remain unchanged. Therefore, the overall conclusion of this research on the effect of implementation of green infrastructure measures on property sales values seems not to be affected by the spatial aggregation of data.

6.2.4 Generalization and Comparability of Results

At last, it is important to note and discuss the generalization of the results of this research. This research has aimed to estimate the effect of the implementation of green infrastructure from a 'just green enough' strategy on property sales values and median gross rent values, and has indeed identified a positive effect on property sales values. Even though this is a promising result, it cannot be generalized; in other words, it cannot be concluded that a 'just green enough' strategy has a positive effect on property sales values – or an effect at all – *per se*, nor can it be concluded that a 'just green enough' strategy has no effect on median gross rent values. Both the case (*i.e.* the New York City Green Infrastructure Project) and the scope (*i.e.* the counties Kings and Queens) that has been used in this research cannot be considered as representable for all 'just green enough' strategies, as such strategies differ to a great extent among one another (*e.g.* in scope, aim, and types and amount of green infrastructure measures). So, even though the results of this research are promising and indicate a positive effect of a 'just green enough' strategy on property sales values, it cannot be generalized in concluding that all projects with a 'just green enough' strategy have the same effect.

Also, it is important to note that the results of this research do not allow for a comparison with green infrastructure projects that do not abide by a 'just green enough' strategy. In other words, the results of this research cannot be used to determine whether projects with a 'just green enough' strategy have a stronger effect on property and rent values than projects that do not abide by a 'just green enough' strategy. Intuitively, due to its scattered and fragmented implementation of green infrastructure, pursuing a 'just green enough' strategy might not lead to increases in prices for real estate as substantial as for projects that do not abide by such a strategy. This can be an angle for future research, which will be discussed in the next section (section 6.3).

6.3 Future Research

This section provides several recommendations for future research directions on the impact of green infrastructure – in particular, a 'just green enough' strategy – on prices for real estate. On the one hand, the recommendations aim to address some of the limitations discussed in the previous section 6.2, whereas on the other hand, recommendations also aim to provide research direction on further examination of the impacts of a 'just green enough' strategy and green infrastructure in general.

First, to overcome the not being able to distinguish between different types of green infrastructure measures from the New York City Green Infrastructure Project, future research can benefit from on the ground research – rather than a desk study – to map the different types of implemented green infrastructure. Also, cooperation with the NYC Department of Environmental Protection can help to be able to distinguish between different implementation times. In doing so, future research would be better able to identify the effects of actual 'green' infrastructure on prices for real estate, as well as be able to make a more deliberate choice for a treatment year. On the ground research also enables to research the possible effects of nuisance of green infrastructure or of its implementation on prices for real estate – something that could not be taken into account within this research.

Second, to further examine the impacts of a 'just green enough strategy' and green infrastructure in general, future research should focus on doing a quantitative analysis – rather than a qualitative. Such an analysis is able to study the actual size of the effect of a 'just green enough strategy' or green infrastructure in general on real estate prices, by taking into account the different attributes that contribute real estate prices in the analysis. As such, a quantitative analysis allows for research on the relative effect of green infrastructure on prices for real estate. Incorporating distance decay in such an analysis will allow for determining the effect of green infrastructure on prices for real estate, whilst also overcoming the spatial aggregation of data on property sales values that has arisen in this research. Furthermore, research on the comparison with projects that do not abide by a 'just green enough' strategy allows for research on the relative effect of a 'just green enough' strategy – compared to projects that do not abide by a 'just green enough' strategy. Together, studying the relative effect of a 'just green enough' strategy and green infrastructure in general gives the findings from this research more meaning.

Furthermore, this research has not been able to determine an effect of green infrastructure implementation on rent values, predominantly due to the existence of rent stabilization in New York City. Future research should therefore also focus on the effects of green infrastructure implementation on rent values – both for projects that pursue and projects that do not pursue a 'just green enough' strategy. However, because research on the effects of green infrastructure on rent values is still scarce, future research should focus on the effects of green infrastructure on rent values in general as well.

Lastly, recent studies have started to identify and emphasize on the possible negative impacts of increases in real estate prices due to green infrastructure implementation: the physical gentrification of neighbourhoods – by means of implementing green infrastructure, making the neighbourhood more liveable and attractive – can lead to social gentrification by altering the housing opportunities for socioeconomic vulnerable, often lower income communities in these neighbourhoods. Future research should therefore also focus more on the socioeconomic and sociodemographic effects of green infrastructure implementation, by studying the effects of increased costs of housing on the (socio-)demographic composition of the neighbourhoods and communities in which green infrastructure is implemented.

7. Conclusion

Research over the past decades has demonstrated that the (physical) health, social, environmental and economic benefits associated with green infrastructure, alongside its aesthetic value, have positive effects on prices for real estate. This research has aimed to identify whether the implementation of green infrastructure according to a 'just green enough' strategy has such an effect on property values as well. By means of a difference-in-difference model with a linear time trend, this research has aimed to identify the effects of a 'just green enough' strategy – in the form of the New York City Green Infrastructure Project – on both property sales values and median gross rent values in the counties Kings and Queens.

Overall, the results presented in section 5.1 and 5.3.1 indicate a positive difference in the level of property sales values between the pre- and post-treatment period for the treatment group, relative to the control group (+17.7% and +10.7% respectively). In other words, these results indicate that there is a positive effect of the implementation of the New York City Green Infrastructure Project on the property sales values. On the other hand, the results presented in section 5.2 and 5.3.2 seem to indicate a negative effect of the implementation of the New York City Green Infrastructure Project on the median gross rent values (−4.2% and −11.9% respectively). However, it needs to be taken into account that the existence of rent stabilization in New York City oppugns the negative effect of the implementation of the New York City Green Infrastructure Project on the median gross rent values, as it prevents the reflection of the impact of the implementation of green infrastructure on rent values by restricting the amount of yearly increase in rent. This makes it difficult to conclude whether there is indeed an effect of the implementation of the New York City Green Infrastructure Project on the median gross rent values and whether this effect is positive or negative.

Altogether, whilst acknowledging the limitations and constraints discussed in section 6.2, this research can conclude that there is a positive effect of the implementation of the New York City Green Infrastructure Project on the property sales values. This also indicates that the implementation of green infrastructure according to a 'just green enough' strategy can have a positive effect – or an effect in general – on property values. However, even though this is a promising result, it cannot be generalized by concluding that a 'just green enough' strategy has a positive effect on property values *per se* – or an effect at all . Nor can it be concluded that a 'just green enough' strategy does not affect rent values. Nevertheless, this research builds on the existing evidence of the impact of green infrastructure on property values by indicating that the same impact applies to a 'just green enough' strategy – at least in the case of the New York City Green Infrastructure Project. Future research should focus on whether the results and conclusion of this research can be generalized. Moreover, future research should focus on the relative effects of green infrastructure from a ‘just green enough’ strategy, as well as focus more on the socioeconomic and sociodemographic effects of green infrastructure implementation.

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Appendices

Appendix I: NYC's Green Infrastructure Project green infrastructure measures

Courtesy of NYC Environmental Protection (n.d. , Types of Green Infrastructure, para. 2-9).

Rain Gardens: *The word rain garden is generally used to describe planted areas that collect rainwater. DEP uses the term rain garden to describe planted areas in the sidewalk that are designed to collect and manage stormwater. Rain gardens are vegetated or landscaped depressions designed with an engineered soil layer that promote infiltration of stormwater runoff into the underlying soil. When it rains, rainwater or "stormwater runoff" flows down the street gutter along the curb and into the rain garden. During a heavy rainstorm, stormwater goes into the rain garden, but some water may go past the inlet and go straight into the catch basin. If the rain garden reaches capacity, the stormwater will overflow at the outlet and go into the catch basin the way it normally would.*

Stormwater Greenstreets: *Stormwater Greenstreets, like rain gardens, are planted areas designed to collect and manage stormwater that runs off the streets and sidewalks. However Stormwater Greenstreets are typically constructed in the roadway, are usually larger than rain gardens, and have varying lengths, widths and soil depths based on the characteristics of the existing roadway.*

Green Roofs: *Green roofs are made up of a top vegetative layer that grows in an engineered soil, which sits on top of a drainage layer. A green roof can be intensive, with thicker soils that support a wide variety of plants, or extensive, covered in only a light layer of soil and minimal vegetation.*

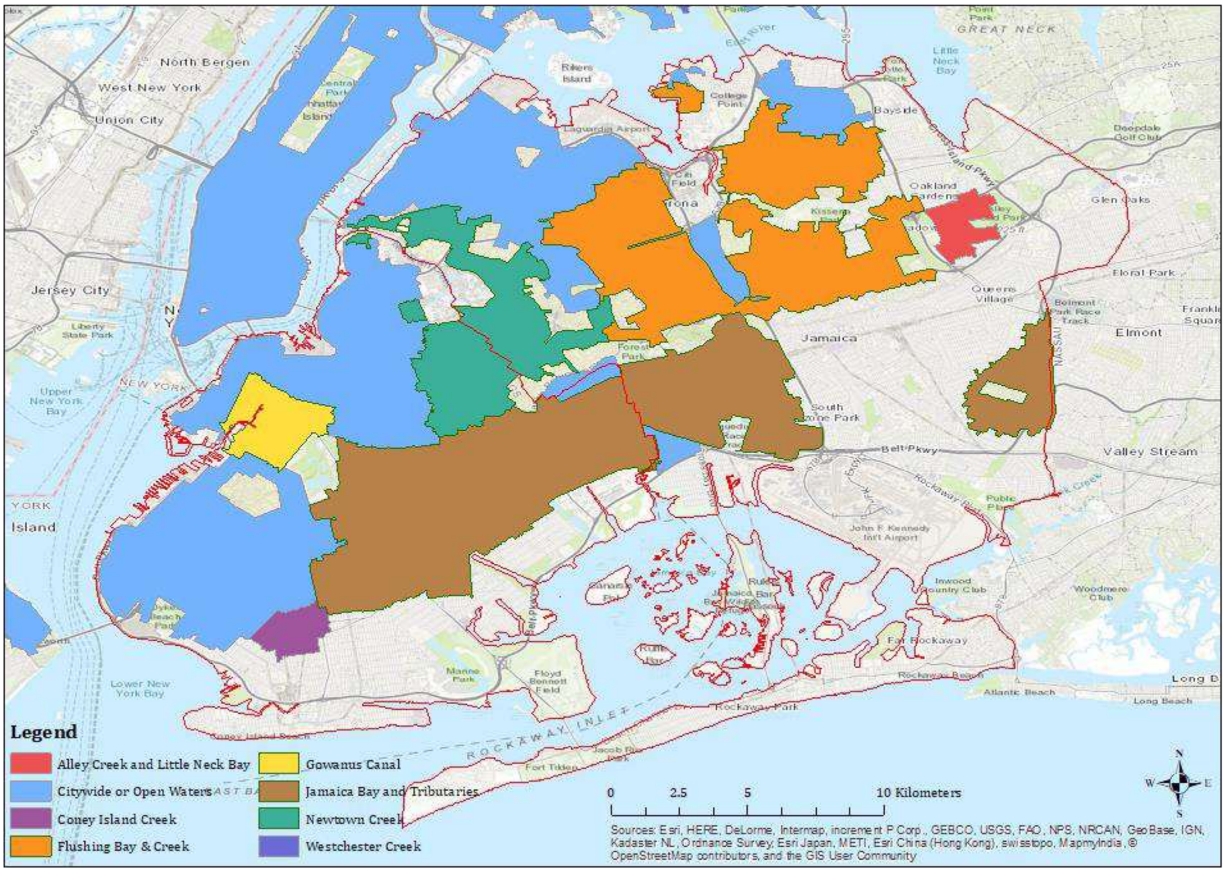
Blue Roofs: *Blue roofs are designed without vegetation for the primary purpose of detaining stormwater. Weirs at the roof drain inlets create temporary ponding and gradual release of stormwater.*

Permeable Paving: *Permeable paving is a range of materials and techniques, such as permeable pavers or porous concrete, which allow water to seep in between the paving materials and be absorbed into the ground. Permeable paving can be used instead of traditional impermeable concrete or asphalt.*

Subsurface Detention Systems: *Subsurface Detention Systems with infiltration capability provide temporary storage of stormwater runoff underground. These systems have an open-bottom and can incorporate perforated pipe and stormwater chambers for added detention volume. Systems are primarily designed with a gravel bed that stores water until it can infiltrate into the ground.*

Rain Barrels and Cisterns: *Rain barrels and cisterns are watertight receptacles designed to catch and store stormwater off of roofs and other impervious surfaces. Cisterns are often larger than rain barrels and can be located underground, at ground level, or on an elevated stand. Rain barrels are connected to the existing downspout of a roof and reuse the stormwater for watering plants and other landscaping uses.*

Appendix II: Priority CSO Watersheds



CSO Watersheds in Kings and Queens counties – outlined in green are the priority CSO watersheds (NYCDEP_KarolinaR, 2018).

Appendix III: Descriptive statistics of property sales values

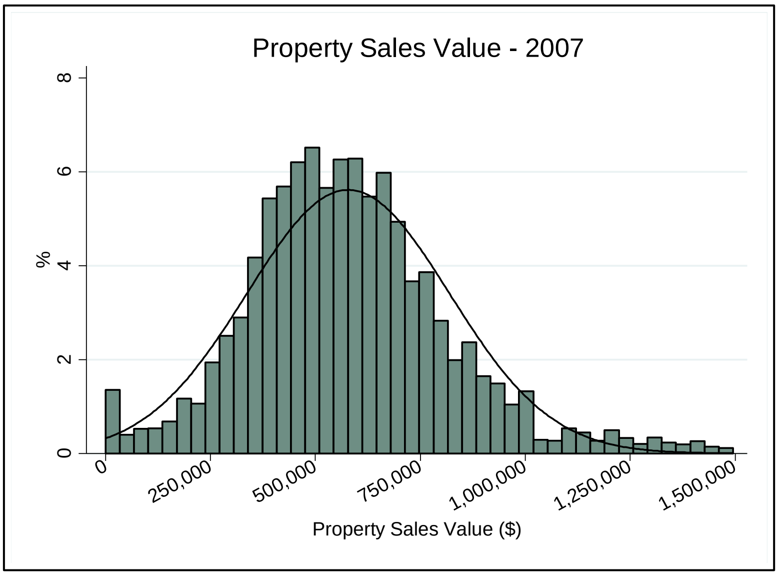
Table 8. Categorical distribution of property sales values

	Freq.	Perc.	Cum.
Price	205,674	100.00	
< \$249,000	21,817	10.61	10.61
\$250,000 – \$499,999	74,338	36.14	46.75
\$500,000 – \$749,999	60,984	29.65	76.4
\$750,000 – \$999,999	28,332	13.78	90.18
\$1,000,000 – \$1,249,999	6,367	3.1	93.27
\$1,250,000 – \$1,499,999	4,454	2.17	95.44
> \$1,500,000	9,382	4.56	100.00

Table 9. Descriptive statistics of property sales values per year

		Mean	Std. Dev.	Obs.
Price		543,501	271,451	196,292
	2007	578,241	241,426	28,307
	2008	540,133	249,661	22,397
	2009	485,122	238,782	19,298
	2010	484,207	245,632	20,842
	2011	498,356	256,534	19,433
	2012	518,271	269,501	19,758
	2013	545,674	283,170	22,246
	2014	586,095	301,871	22,051
	2015	627,411	311,675	21,960

Notes: Data cover time period from 2007 to 2015 and property sales values lower than \$1,500,000 – representing > 95% of the data.


Property Sales Value - 2007
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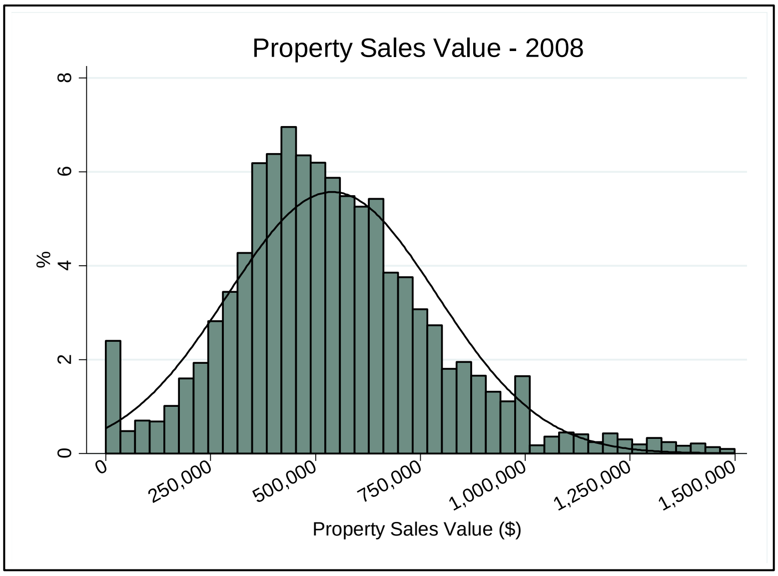
Property Sales Value ($)

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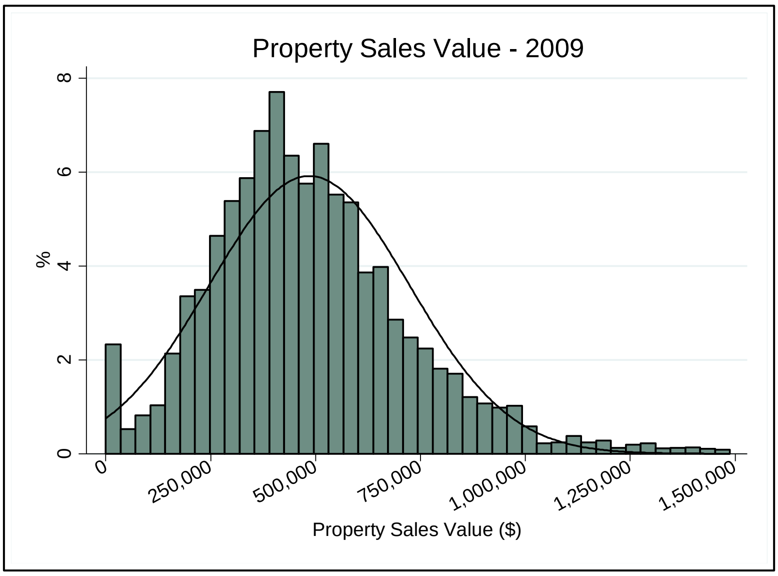
Property Sales Value ($)

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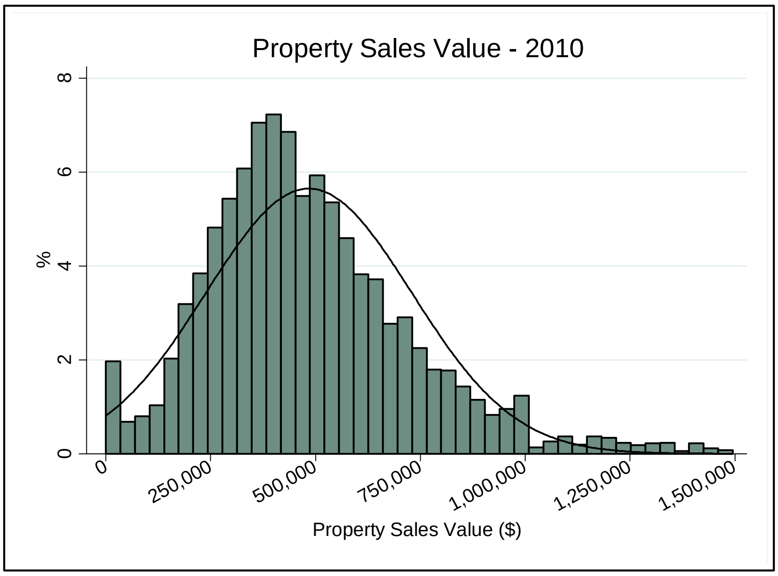
Property Sales Value - 2010
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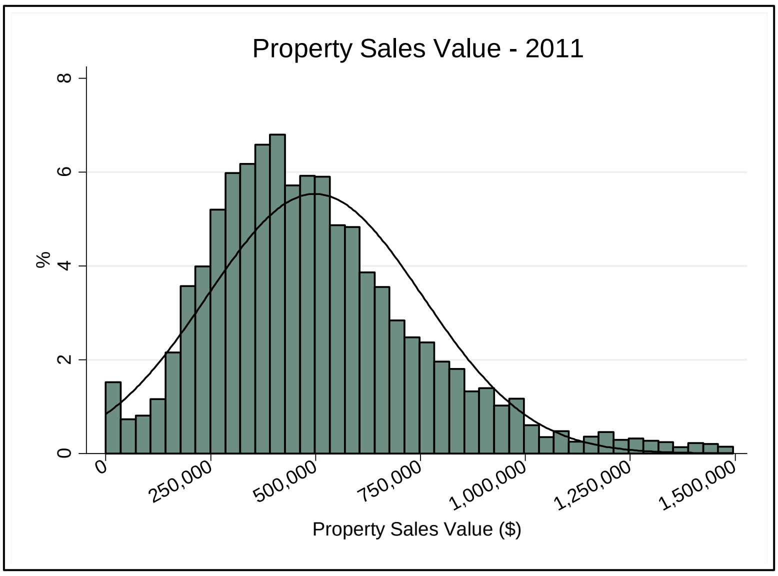
Property Sales Value ($)

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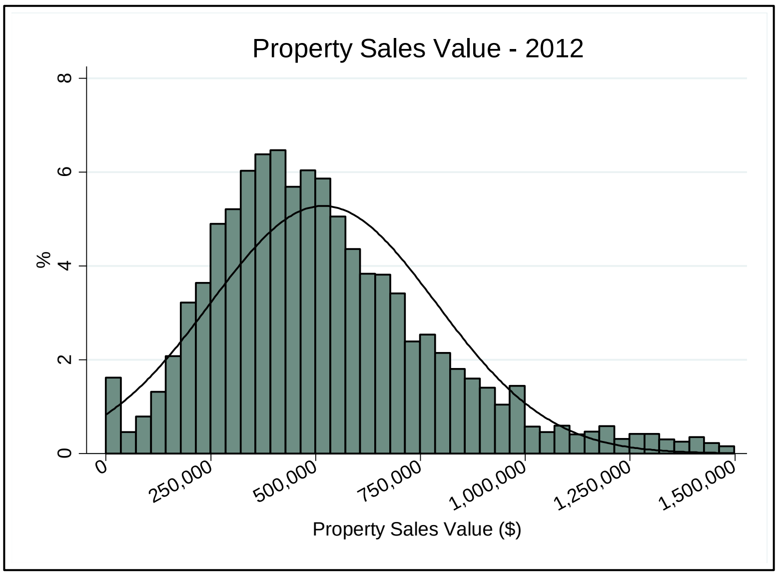
Property Sales Value ($)

Property Sales Value - 2012
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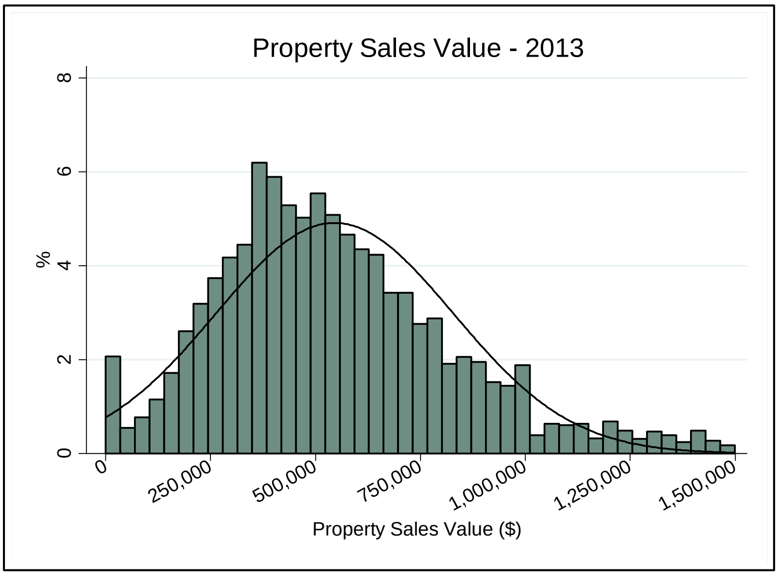
Property Sales Value ($)


Property Sales Value - 2013
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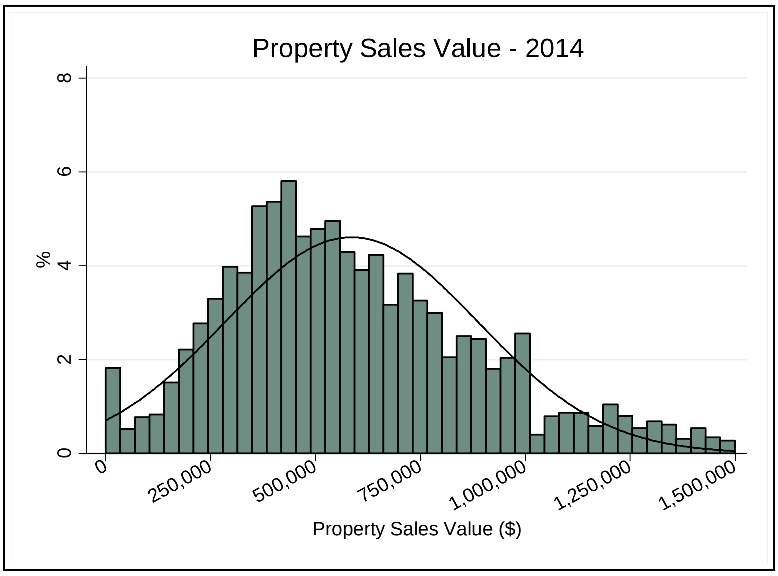
Property Sales Value ($)


Property Sales Value - 2014
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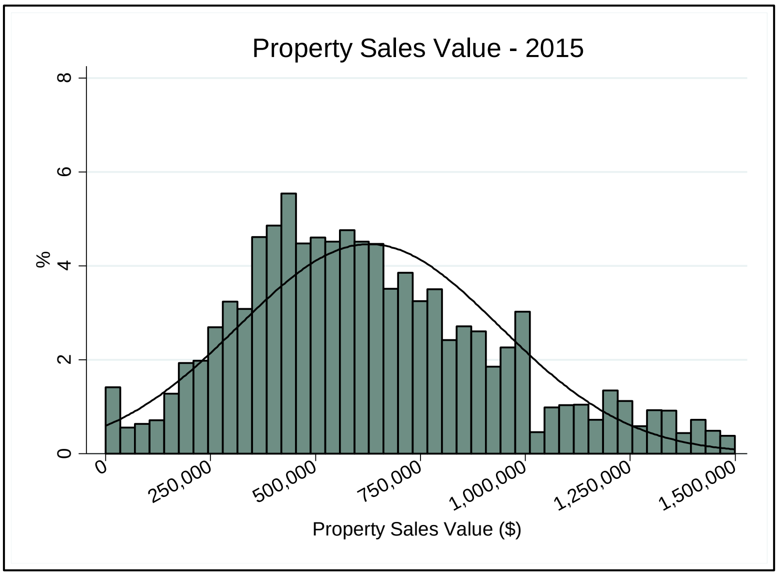
Property Sales Value ($)


Property Sales Value - 2015
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1,500,000
Property Sales Value ($)

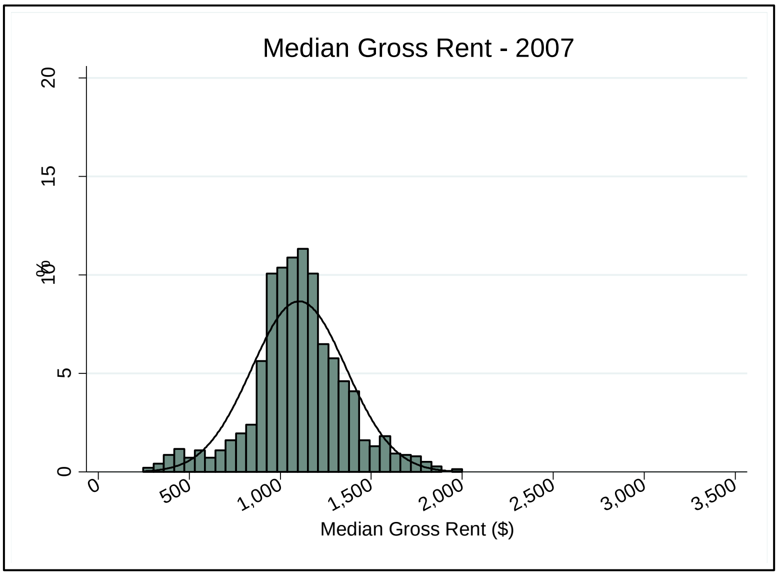
Appendix IV: Descriptive statistics of median gross rent values

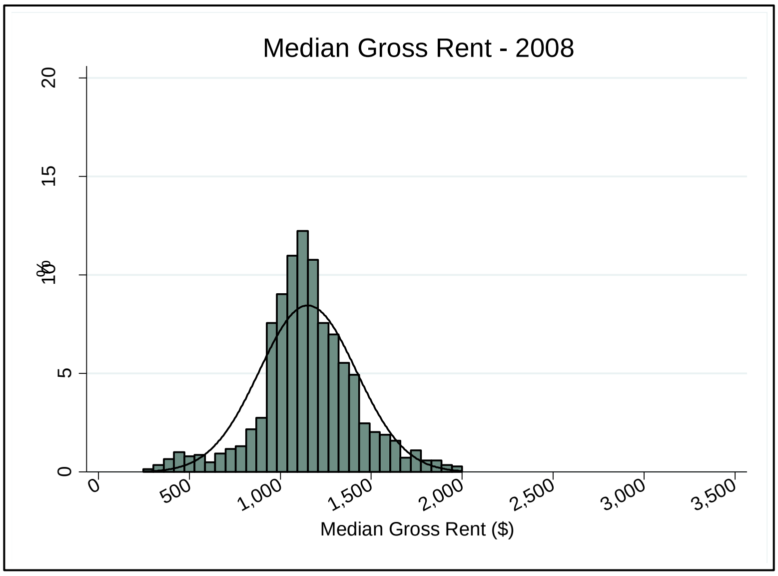
Table 10. Categorical distribution of property sales values

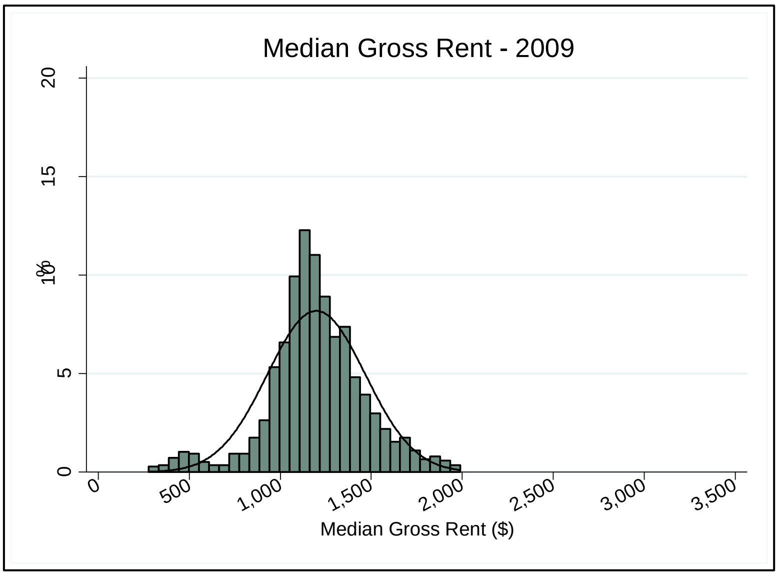
	Freq.	Perc.	Cum.
Median Gross Rent	12,287	100.00	
< \$500	251	2.04	2.04
\$500 – \$749	354	2.88	4.92
\$750 – \$999	1,063	8.65	13.58
\$1,000 – \$1,249	4,199	34.17	47.75
\$1,250 – \$1,499	4,203	34.21	81.96
\$1,500 – \$1,749	1,550	12.61	94.57
\$1,750 – \$1,999	471	3.83	98.4
> \$2,000	196	1.60	100.00

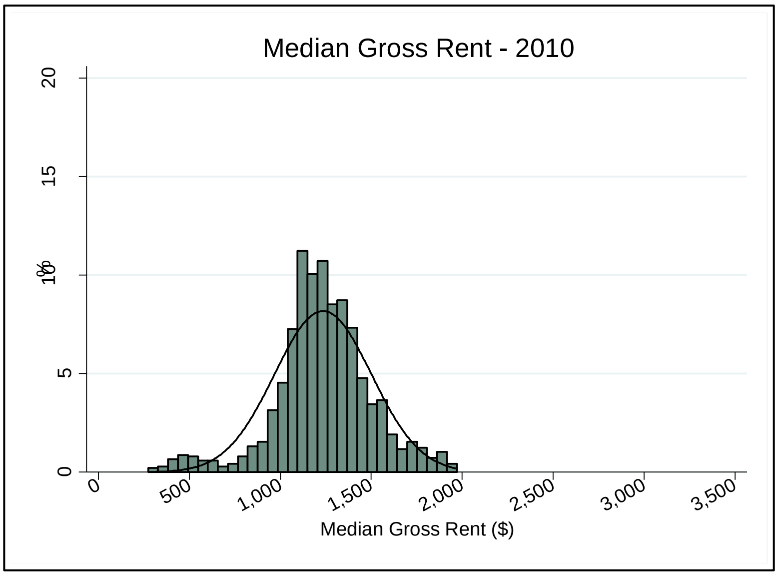
Table 11. Descriptive statistics of median gross rent values per year

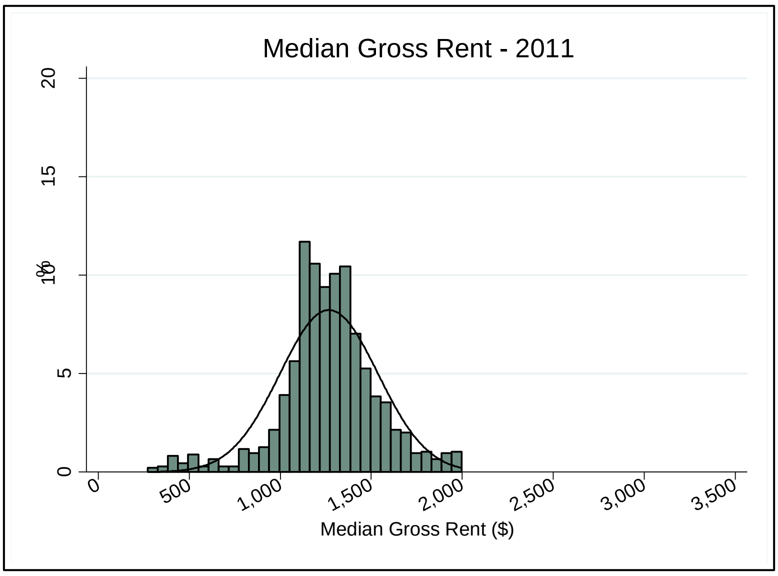
	Mean	Std. Dev.	Obs.
Median Gross Rent	1271	310.85	12287
2007	1103	260.31	1369
2008	1151	266.93	1374
2009	1198	269.35	1368
2010	1235	267.24	1362
2011	1268	269.85	1351
2012	1296	269.50	1337
2013	1351	322.49	1377
2014	1392	332.18	1378
2015	1444	353.86	1371

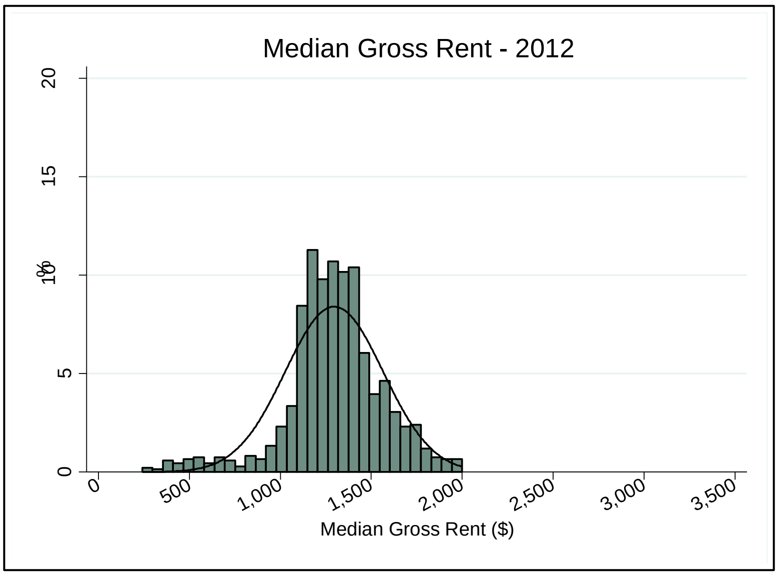

Median Gross Rent - 2007
%
0
5
10
15
20
0
500
1,000
1,500
2,000
2,500
3,000
3,500
Median Gross Rent ($)

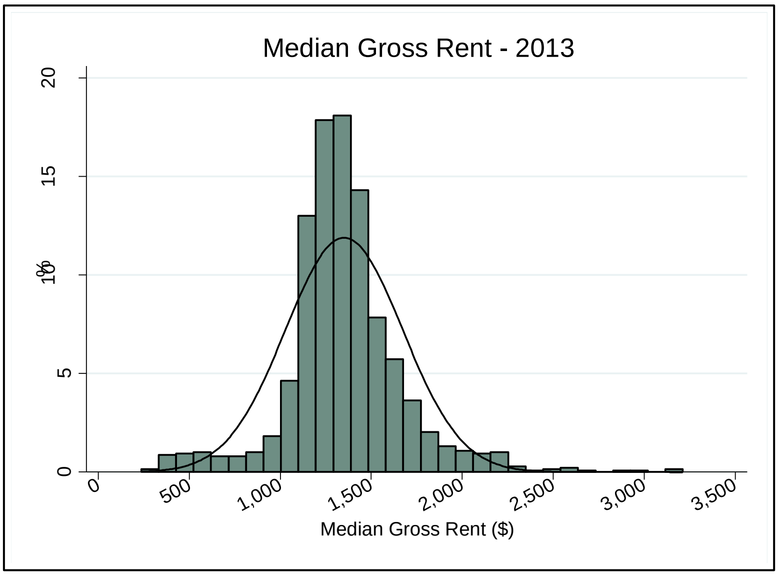

Median Gross Rent - 2008
%
0
5
10
15
20
0
500
1,000
1,500
2,000
2,500
3,000
3,500
Median Gross Rent ($)


Median Gross Rent - 2009
%
0
5
10
15
20
0
500
1,000
1,500
2,000
2,500
3,000
3,500
Median Gross Rent ($)

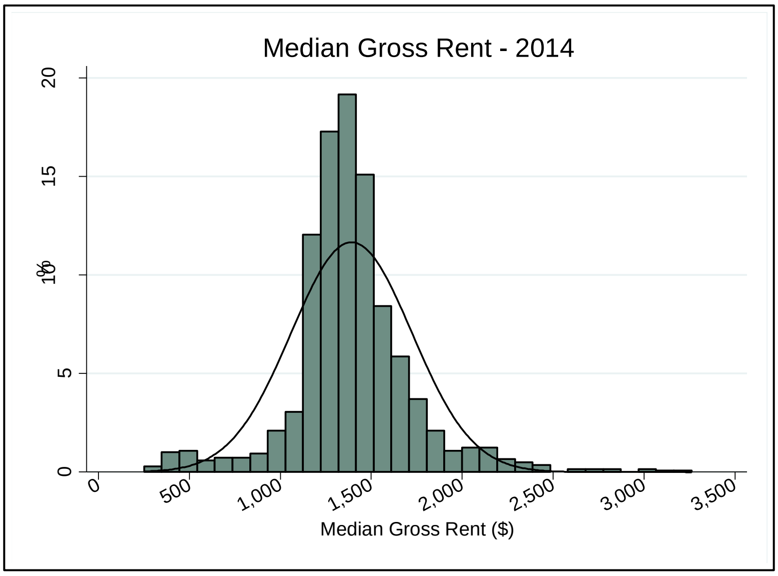

Median Gross Rent - 2010
%
0
5
10
15
20
0
500
1,000
1,500
2,000
2,500
3,000
3,500
Median Gross Rent ($)


Median Gross Rent - 2011
%
0
5
10
15
20
0
500
1,000
1,500
2,000
2,500
3,000
3,500
Median Gross Rent ($)

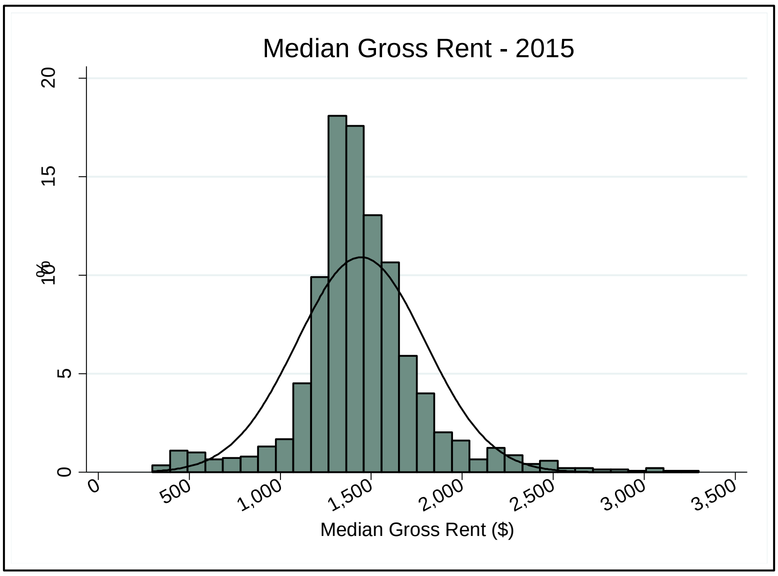

Median Gross Rent - 2012
%
0
5
10
15
20
0
500
1,000
1,500
2,000
2,500
3,000
3,500
Median Gross Rent ($)



Median Gross Rent - 2013
%
Median Gross Rent ($)

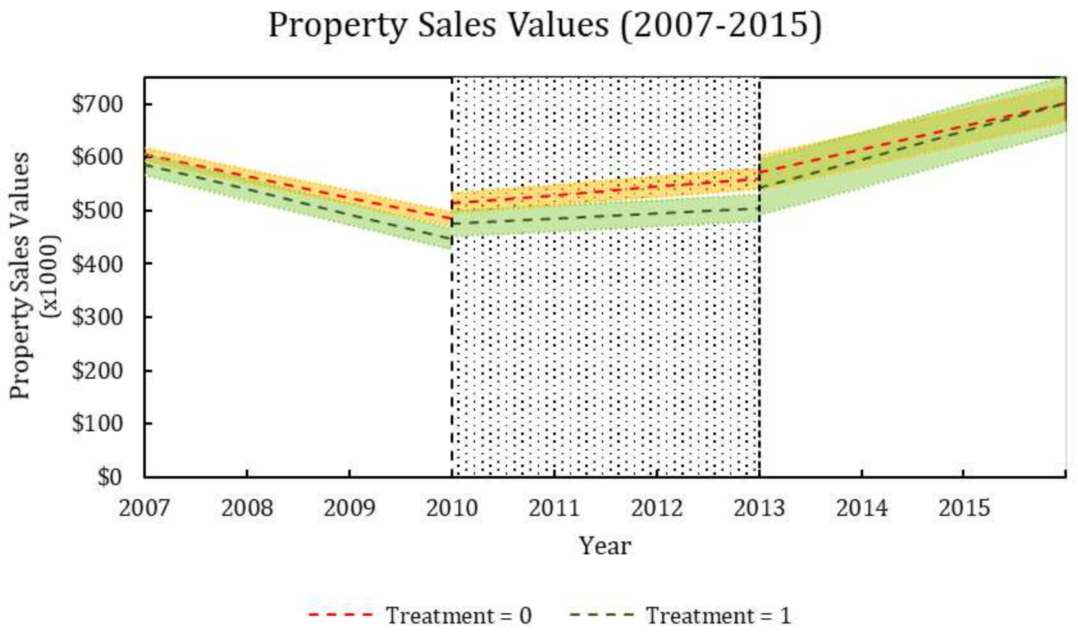


Median Gross Rent - 2014
%
Median Gross Rent ($)

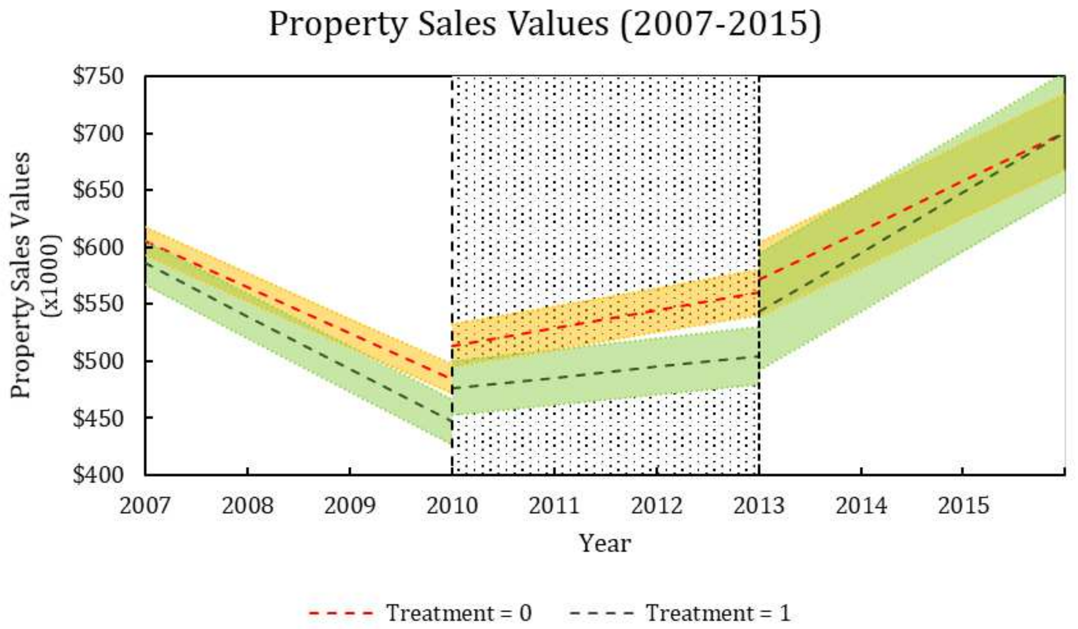


Median Gross Rent - 2015
%
Median Gross Rent ($)

Appendix V: Graphs sensitivity analysis – property sales values

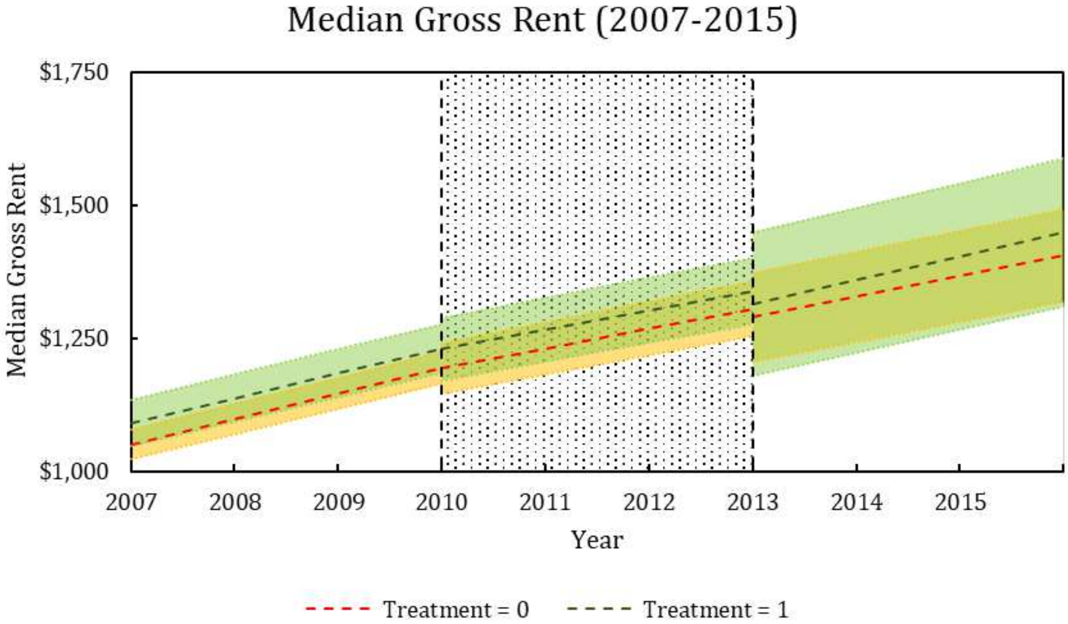


Graph 6. Visual representation of the estimation results of the sensitivity analysis for property sales values (2007-2015).



Graph 7. Visual representation of the estimation results of the sensitivity analysis for property sales values (2007-2015).

Appendix VI: Graphs sensitivity analysis – median gross rent values



Graph 8. Visual representation of the estimation results of the sensitivity analysis for median gross rent values (2007-2015).