Short-term rentals and the housing market

A research on the effect of Airbnb on the housing prices in Amsterdam.

This thesis is written as a final assignment for the Master of Real Estate at the Amsterdam School of Real Estate.

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Abstract

Affordable housing and housing shortage have become a major issue in several world cities. Many politicians accuse platforms like Airbnb for putting pressure on the already overheated housing market. This research estimates the effect of Airbnb listings on the property prices in Amsterdam by applying a regression discontinuity model. The model is based on two groups: a group of transactions that has an Airbnb within a radius of 150-meters and a group that does not have an Airbnb nearby. Opposite to the more commonly used difference-in-difference approach, the regression discontinuity model allows to control for unobserved neighborhood effects and thereby prevents overestimating of the effect. The results imply an increase of 3.6% of the property prices that have an Airbnb within a 150-meter radius in the period 2008-2018. Additionally, within the same time period, an increase of 10.6% of property prices is found that have an Airbnb within a 500-meter radius. An important conclusion of this research is that per year the effect of Airbnb on the housing prices increases, as does the density of Airbnb. To limit further pressure on the market, policy makers should focus on finding the maximum amount of Airbnb listings in certain areas to limit the effect of increased housing prices, while still meeting demands from the tourist industry.

Keywords - short-term rentals, house prices, externalities, regression discontinuity, regulations

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Acknowledgement

Two years ago, the Central Government Real Estate Agency gave me the opportunity to follow the Master of Real Estate at the Amsterdam School of Real Estate. After working in the real estate branch for multiple years with a background in urban planning, I realized that I needed a more solid basis in real estate. In order to create realistic (re)development plans that are financially feasible for my clients, I needed a better understanding of the different actors in the market and their incentives to invest in my projects. This research concludes this master program.

The topic for this research came out of personal interest. All my life I have travelled around the world to discover new places and meet new people and cultures. Even during this master's degree, I was lucky enough to be able to keep travelling as much as before. During my travels I was always looking for small places and bed and breakfasts to stay, to get a more authentic experience. In 2011, for the first time I started using Airbnb during my stay in San Francisco. I loved the personal touch and local feel of Airbnb. It allowed me to meet local people, get to know how life in that place is and visit neighborhoods that where off the tourist radar. There were local coffee places, small shops and stores that made those places authentic. However, over time the amount of Airbnb locations grew significantly while the personal touch disappeared quickly. I noticed that Airbnb was popping up everywhere and it made me realize that it also changed places. All of a sudden, in those previously authentic neighborhoods with their own identity, global chains started to pop up. It made me think about the effect of tourism and Airbnb on those places. It was clear to me that further investigation was needed.

I would like to thank all my friends and family that have motivated me and helped me in the past two years when I really needed it. They always knew when to drag me from behind my computer and cheer me up when I got stuck with this thesis. Without their endless positive energy, I would not be here, writing my final words for this thesis. Thanks to all the people that helped me with the technical programs STATA, Excel and QGIS, especially Robin Huizinga and Douglas Konadu. Martijn Dröes, thank you for making everything sound so easy while it really was not. You are a great supervisor that has always been available for help. Your input, feedback and knowledge were of great value for this thesis.

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1. Introduction

In the past ten years, Amsterdam has become one of the least affordable cities to live in the Netherlands. UBS placed Amsterdam on the 5th place of world cities with potential real estate bubbles and stated that property prices in the city have soared by 45% in the last three years (UBS, 2018). Since 2013 prices have even increased by 60%. The city's housing price rise has more than doubled the nationwide averages in the last five years making the city unaffordable for many to live. An average house in 2018 in Amsterdam costs €448,000/ €5,129 per m2, while in the rest of the Netherlands an average house costs €298,000/ €3,111 per m2 (RTLZ, 2019; Couzy & Damen, 2018). Within this period, renting prices have increased significantly as well to an average renting price of €15.30/ m2 in 2018 (Pararius, 2018). Due to this, rents continue to consume a substantial share of income of those who live in the city (UBS, 2018).

Many people, among other politicians blame speculators, investors and the tourist industry for the shortage of houses and steep rise in prices (Valentine, 2019; Couzy, 2018). They believe that the aforementioned actors are aggregating pressure on the already overheated housing market by buying real estate as an investment. Policymakers therefore aim to regulate economic behavior in such ways that it becomes less interesting for them to invest in these markets; hereby aiming to release pressure on the housing market. Practice shows that it is very difficult to regulate behavior of such actors and making it less interesting for them to invest in these cities. Therefore, Amsterdam and seven other cities collaboratively asked the United Nations for help in dealing with the problems of overcrowded city centers and overheating housing markets. In a letter to the UN, written by the mayors of metropoles Amsterdam, Barcelona, London, Paris, Berlin, New York, Montreal and Montevideo they demand for '…morel legal and fiscal power to regulate the real estate market in order to fight against speculation and to guarantee the social function of the city'. They demand for more effective policy instruments to protect renters, maintain affordable houses in metropoles and deal with companies like Airbnb that distort the market (Couzy, 2018; Pieters, 2017). Regardless of this demand for help no solution is found yet.

In the recent debates on affordable housing, a lot of emphasis is placed on the growth of contemporary urban tourism and the effect of peer-to-peer platforms like Airbnb on the housing market (Segú, 2018). The affordable housing crisis has emerged alongside the transformation of the tourism sector. Tourism in Amsterdam has grown incredible. In 2008 Amsterdam counted little below 7 million tourist that visited the city while in 2018 this amount almost doubled to a dazzling number of 14 million people that stayed in Amsterdam (OIS, 2018). The growth of the tourist sector went hand in hand with the emergence of the short-term rental market: the rental of entire apartments or rooms to tourist arranged through Airbnb and other peer-to-peer platforms. Airbnb now has a 10.4% market share in Amsterdam in the hotel sector and has become an important player for the sector. Due to the high demand of hotel rooms, fueled by the increasing stream of tourist, the different suppliers of tourist accommodation seem to be able to coexist. Opponents argue that the already overheated housing market, in combination with the increasing stream of tourists and the emerging of platforms like Airbnb brought tourist into direct competition with renters and buyers, thereby distorting the housing market (Lee, 2016).

Airbnb is a company that facilitates short-term rentals by providing a platform for users to rent out their private residential homes or rooms (Lee, 2016). Concerns about the negative consequences of Airbnb on the housing market and the pressure exerted by the increased tourism have driven many cities to impose (local) regulation that limit the holiday renting market (Segú, 2018; Gurran & Phibbs, 2017). Measurements include limiting the rental period per year, paying rental tax, requiring permits or even making it illegal to rent out private houses to tourists. Amsterdam for example has limited the maximum days of renting out an apartment to 60 days since January 2017. This amount has been further limited to 30 days in 2019. In regulation, a distinguish is often made between two types of short-term rentals: home sharing where the host lives in the apartment during the stay of visitor and vacation rentals, which are for exclusive use of visitors (Van Ommeren, e.a., 2019). Regardless the regulation, the short-term rental market keeps growing and spreading over the city, even to the suburb and neighboring towns. Although Airbnb in 2018 for the first year ever registered a 5% decrease in bookings, new short-term rental platforms emerge on the market. For example, the platform HomeAway that grew with 61% in the last year (Bakker & Kuijper, 2018).

According to the research of Colliers (2018), now 7.989 houses/ apartments are subtracted from the market. These houses/ apartments are used for short-term rental for more than 60 days per years, regardless of the regulation by the government. Houses rented out for more than 60 days per year cannot be rented or bought by permanent residents and are thus subtracted from the market. Expectations are that house owners in more touristic areas will more likely convert their property into Airbnb's because of the profits they can generate by doing so. Thereby, reducing the supply of houses available for sale and long-term rent. Many people argue that this pushes up the prices of remaining houses and stimulates further transformation of residential houses into tourist accommodation (Meranta & Horn, 2016; Sheppard & Udell, 2016; Barron e.a., 2018). If this is the case it would affect the city in many ways. Because Airbnb does not provide addresses of Airbnb hosts it becomes incredible difficult for governments to enforce their own laws.

Besides the subtracting of properties from the market, the short-term rental market also has many other negative externalities. Airbnb is blamed for decreasing affordability of cities, noise disturbance, traffic- and parking problems and waste in de streets caused by tourists. Some also argue that Airbnb leads to gentrification of neighborhoods in the city, pushing away local people and businesses. One could argue that these externalities could have a negative impact on the housing prices. On the other hand, there are also advocates of short-term rental market. They argue that the short-term rental market has a positive economic impact on the city by creating new income streams for residents as well as encouraging tourism and its associated economic benefits for a city (Gurran & Phibbs, 2017).

With all the above taken into account, the aim of this research is to give insight in the potential effect of Airbnb on the housing market in Amsterdam. This research will answer the following main question: 'What is the effect of Airbnb on the housing market in Amsterdam in the past 10 years?'. In many contentious debates on affordable housing the finger is pointed towards Airbnb. However, there is still a shortage of empirical research trying to assess the consequences of Airbnb and how big the effects are exactly. While the literature on Airbnb is significant and growing, this research aims to fill that void and fuel the debate with empirical evidence. Previous empirical research shows that Airbnb has an upward effect on the housing prices. Latest research from Koster e.a. (2019), studied the effect of platform like Airbnb on the housing market. Their estimates imply large effects of Airbnb on property values in areas attractive to tourists. In downtown Los Angeles an increase of 10% is found. Sheppard & Udell (2016), argue that housing prices increase by 31% due to Airbnb. Barron et al. (2018) found a moderate effect of Airbnb on both the housing and renting prices. Horn & Merante (2017) found that one standard deviation increase in Airbnb listings is associated with an increase in asking rents of 0.4%. Also, studies in Barcelona to the effect of Airbnb there on the renting prices show a positive and significant effect on the renting prices (Garcia-Lopez et al. (2018). However, these researches suffer from endogeneity issues; as neighborhoods become more attractive to residents, they also become more attractive to tourist. Most researchers measure the effect of Airbnb by looking to the density of Airbnb. One could argue that, those neighborhoods with a high density of Airbnb's are also of interest to residents because of certain characteristics that make the neighborhood attractive. They, for example, have more amenities and landmarks such as parks, monuments and playgrounds or even a certain vibe in the area that drives up property prices.

Also, by measuring the effect of Airbnb with a difference-in-difference approach, like previous researchers, these endogeneity issues are not taken into account. Black (1999) argues in her study to the quality of schools that, often if one does not carefully control for neighborhood characteristics, one will greatly overestimate the value of the additional school quality (Black, 1999). Conceptually, this research will use the methodology of Black (1999). Black (1999) used a regression discontinuity model in her research to estimate the value that parents place on school quality by calculating how much more people pay for houses located in areas with better schools. Black (1999) compared houses on opposite sides of attendance district boundaries, the geographic lines that determine which school a child attends within a school district. By defining a border or sharp line it is possible to notice 'jumps' in test scores at attendance district boundaries, while neighborhoods continue to change in a smooth manner, thereby isolating the relationship between test scores and house prices. In her research, she limited the sample to houses that are very close to the attendance district boundaries. Those houses were within close proximity of each other, but children attended different schools. This allowed her to control for neighborhood differences (Black, 1999). Her findings show that houses within 0.15 miles from the border result in a 5 percent increase in test scores lead to a 2.1% increase in housing prices. This amount is half the estimate of a typical hedonic housing price regression.

Because of this risk of overestimating the effect of Airbnb on housing prices, this research, in line with the research of Black (1999) uses a quasi-experimental regression discontinuity model that aims to isolate the effect of tourism demand on the housing prices more accurately. By creating areas in Amsterdam where Airbnb is present, and areas where Airbnb is explicitly not present, the research intents to compare price changes in areas with and without the appearance of Airbnb and thereby overcoming these endogeneity issues. In order to do this a 150- and 500-meter buffer around every Airbnb is placed to filter out unobserved neighborhood effects. Every transaction either falls in or outside the buffer. Then, by using a regression discontinuity model, the transaction price development of the two groups are compared over three periods of time. First of all, a regression of the period 2000-2018 is done which estimates the impact of the introduction of Airbnb on the transaction prices. Secondly a regression is done for the period 2008-2018. This is the period Airbnb was active in Amsterdam. Last, a regression is done per year that Airbnb was active in order to see if the effect increases over time and to what extent. Additionally, as a robustness check also the 500-meter distance is checked.

The results imply an increase of 3.6% of the property prices that have an Airbnb within a 150-meter radius in the period 2008-2018. Additionally, within the same time period, an increase of 10.6% of property prices is found that have an Airbnb within a 500-meter radius. An important conclusion of this research is that per year the effect of Airbnb on the housing prices increases, as does the density of Airbnb. To limit the effect policy makers should focus on finding the maximum amount of Airbnb listings in certain areas to limit the effect of increased housing prices. The finding of this research can help policy makers to formulate more targeted laws and policy. As the municipality is dealing with an ever-increasing stream of tourists, a balance needs to be found where on the one hand the negative effect on the housing market are limited while on the other hand people are able to rent out their apartment/ room for times when they are not using it, to accommodate tourists.

This research has the following structure. First of all, the theoretical framework will give more insight in the emergence of Airbnb and the contemporary debate on the externalities of the short-term rental market. The second part of the theoretical framework discusses literature that study the effect of externalities on housing prices. The theoretical framework is followed by the chapter Data and descriptives where the two datasets of this research are described and analyzed. Chapter 4 discusses the research method and elaborates on the applied regression discontinuity model, based on the theoretical framework and available data. The results are discussed in the chapter 5, followed by an outline of the limitations of this research and suggestions for future research in chapter 6. The conclusions are presented in chapter 6. In this last chapter the main question of this research is answered, and suggestions are done for regulations.

2. Theoretical framework

This part of the research will provide some background information on Airbnb. After this, the main points in the contemporary debate on Airbnb and other home-sharing platforms are discussed followed by an overview of different studies to Airbnb. Next, scientific research is examined that aims to measure the effect of externalities on the housing prices. The different methods used in these researches are considered and compared and form the basis for the applied methodology.

2.1 Airbnb and the contemporary debate

Airbnb is a peer-to-peer online home sharing platform that facilitate matching between demanders and suppliers of hotel rooms. It is an example of the 'sharing economy'; an economic concept that advocates on sharing goods and services (Kenton, 2019). This is often facilitated by a community based online platform. Airbnb charges a fee to both the host and guest. Airbnb was founded in 2008 and has grown rapidly over de last few years. It has now over 2 million listings in over 190 countries and 34,000 cities. Airbnb hosts have hosted over 40 million guests and the company is now worth an estimated 25.5 billion (Jefferson-Jones, 2015). The highest concentration of Airbnb listings is located in Paris, France (78,000) followed by London, UK (47,000) and New York, USA (46,000). Amsterdam has around 19,619 listing. The founders of Airbnb, Joe Gebbia and Brian Chesky, were struggling to pay their rent in San Francisco. They came up with the idea to rent out airbeds on their living-room floor and cooking their guests breakfast in return for a small fee that helped them pay their rents (Gallagher, 2017). With this history taken into account it is almost ironic that Airbnb is now blamed for fueling the current affordable housing crisis and pushing up the prices in cities even more.

The affordable housing crisis has emerged alongside the transformation of the tourism sector. Tourism in Amsterdam has grown incredible. In 2008 Amsterdam counted little below 7 million tourist that stayed in the city while in 2018 this amount almost doubled to a dazzling number of 14 million people that visited Amsterdam (OIS, 2008). The growth of the tourist sector went hand in hand with the emergence of the short-term rental market: the rental of entire apartments or rooms to tourist arranged through Airbnb and other peer-to-peer platforms. Opponents argue that the already overheated housing market, in combination with the increasing stream of tourist and the emergence of platforms like Airbnb brought tourist into direct competition with renters and buyers, thereby distorting the housing market (Lee, 2016; Barron e.a., 2018).

Many researchers argue that Airbnb reduces the affordable housing supply by distorting the housing market in two ways. First of all, Airbnb leads to conversion: any house that was previously occupied by a city resident and now is listed on Airbnb year-round is a unit that has been removed from the market and has been added to the supply of hotel rooms in any given city. Expectations are that this will most likely lead to increase in housing prices in cities, specifically in those areas close to tourist attractions and gentrifying neighborhoods (Lee, 2016; Gurran & Phibbs, 2018; Merante & Horn, 2016). The second way Airbnb distorts the housing market is that is becomes economically more beneficial for a property owner or leaseholder to rent out a room on Airbnb than to rent it out on the residential market. After all, a room on Airbnb often has a cheaper price than a hotel room which attracts the many tourist that are visiting Amsterdam, while earnings from the short-term rental market are substantially higher than in the residential market. Property owners are more willing to switch from supplying the residential market to supplying the short-term rental market in which non-residents are more likely to participate (Barron e.a., 2018). This is in line with the maximization theory; people will make decisions based on the for them economically most profitable outcome (Muller, 2014; Meranta & Horn, 2016; Lee, 2016; Barron e.a., 2018).

Based on these two assumptions we can argue that some portion of the housing stock listed on Airbnb would otherwise have been occupied by tenants, thereby decreasing the supply and increasing the prices of the rental housing units listed for rent. Similarly, this theory also suggests that owners' or tenants' expectations of being able to earn income by subletting their unit through sharing, will increase the demand for long term rental housing (Meranta & Horn, 2016; Sheppard & Udell, 2016; Barron e.a., 2018). Airbnb draws both private and commercial actors to purchase residential properties as investment, and to hold on to properties for longer periods because rental income obtained via Airbnb reduces the costs of ownership.

According to research from ING bank (2016) Airbnb in Amsterdam generates approximately € 350, - (net) extra income per month for homeowners, by renting out their houses or a spare room based on the maximum of 60 nights per year. Gurran and Phibbs (2017) argue in their research that households may gain almost a fifth of their median monthly rental or mortgage costs. Airbnb can in this way been seen as an opportunity for citizens to raise additional income. In theory, this potential increase in income could allow for a mortgage of approximate €100.000, - more per house, resulting in higher house prices (ING, 2016; Sheppard & Udell, 2016). Some tenants will obtain housing in excess of the amount that would have maximized their property value (Merante & Horn, 2016). The research states that house buyers are willing to pay more money because of the possibility to generate extra income. In addition, house owners demand more for their house because of the extra income generating possibility. However, there are some critical notes on these researches. House buyers might not be willing to value the complete renting price into their offer, or even not at all. For example, research to land lease prices shows that people often do not value whether or not the land lease price is paid off when making an offer on a house (Baarsma & Van Dalen, 2016). In addition, homebuyers might take into account the risk that governments in the future will regulate platforms like Airbnb more strictly and thereby threatening the potential income generating effect (ING, 2016). Moreover, regulations prevent banks from including future rental income into the mortgage calculation.

Proponents of the short-term rental market argue that, besides extra income, those who rent out a spare room or supply their entire home during temporary absences provide extra rooms to accommodate the larger demand from tourists. These otherwise vacant rentals are used as vacation homes that would not be rented to long-term tenants because of the restrictiveness of long-term leases. In either case, these owners would not make their homes available to residents, independently of the existence of convenient house-sharing platform. Instead, home sharing provides them with an income stream for times when their housing capacity would otherwise be underutilized (Gurran and Phibbs, 2017). Thus, the positive effect is a larger supply of accommodations for tourists in Amsterdam and extra income for homeowners. However, the big losers are starters on the housing market and people from outside these urban areas that want to move in (ING, 2016). Due to increasing housing prices and local prices, they are not able to find and finance a house in these areas.

Not only does Airbnb potentially affect housing- and renting prices, Airbnb is also blamed for many other externalities. Critics argue that Airbnb disrupts cities by pushing away residents out of their neighborhood and breaking up communities. People complain about the perception that different tourists occupy the premises each week which gives a feeling of unease due to the changing tide of faces (Richardson, 2015; Lee, 2016). Moreover, Airbnb seems to have a higher density in those areas submissive to gentrification and is accused for contributing to the gentrification of cities (Lee, 2016). Gentrification occurs when rising house prices and rents displace the neighborhoods lower income household, who are replaced by wealthier residents that change the districts' essential character (Lee, 2016). In these cases, they are replaced by (private) investors that transform the houses into short-term rentals. As a consequence, local shops disappear and a very monotonous streetscape appears with many (chain) coffee shops and tourist facilities, losing the original identity and characteristics that made those neighborhoods so attractive in the first place. Critics argue that home sharing platforms like Airbnb raise the costs of living for local renters, while mainly benefitting local property owners and non-resident tourists (Barron, 2018). Besides this, many argue that Airbnb and other short-term rental platform can lead to noise, nuisance and increase in traffic, parking- and waste management issues and increased crime levels. Due to Airbnb, tourism pops up in residential areas that are not designated for tourism. The lack of laws and policies on Airbnb and other home sharing platforms leads to complaints from neighbors. Many home owner associations therefore agreed to not allow Airbnb within the building. One could argue that, since Airbnb imposes a substantial number of negative externalities on the surrounding as well, it could also have a negative effect on the housing prices in areas.

2.2 Externalities and housing prices

Numerous people have studied the effect of externalities on the housing prices, other than individual house characteristics. For example, Dröes & Koster (2016) measured the external effect such as noise, flickering and shadows of wind turbines on the transaction prices of nearby houses by using a difference-in-difference approach. Typically, a difference-in-difference approach has a treatment and control group. Difference-in difference research compares the change in outcomes pre- and post-treatments, thereby adjusting for differences in pre-treatment values of Y in the two groups (Stock & Watson, 2015). In this research the treatment group measures the effect after the first wind turbine is constructed within a certain distance of a property. They experimented with different control groups located closely and further away from wind turbines. Dröes & Koster (2016) found that, on average, house prices decrease by 1.4% after the construction of a wind turbine within a 2 km distance from a property. Housing prices are already statistically significant lower 2 years before the placements. After 10 years, still a 2.2% decline in price is still visible. Koster & Van Ommeren (2015) did a similar type of research by looking to negative external effects of natural gas extraction on the house prices. They found that earthquakes have a negative effect on house prices of about 1.2%. Dekkers & Van der Straaten (2009) developed a spatially-explicit hedonic pricing model for house prices in order to quantify the social costs of aircraft noise disturbance in monetary terms. Based on the regression results they concluded that a higher noise level means a lower house price. Of all traffic types, aircrafts have the largest impact on house prices. Theebe (2002) found in his research that the maximum impact of traffic noise is a 3 to 10 % house price reduction.

Although the company Airbnb does not provide data for research, studies have been done that measure the effect of Airbnb on the housing prices and other externalities aiming to shift the theoretical debate towards a more empirical grounded debate. For example, Sheppard and Udell (2016) did research to measure the effect of Airbnb on the housing prices in New York by using a hedonic regression model. They found that a doubling in Airbnb listings is associated with increases of 6% to 11% in property values. Besides a basic regression, they used a difference-in-difference approach, which resulted in an even larger estimated impact of 31% increase in house prices when Airbnb was available within a buffer of 300m around a house transaction. Van der Bijl (2016) studied the effect of Airbnb on the housing prices in Amsterdam by using a similar model. He found that house prices in Amsterdam increase by 0.42% per increase in Airbnb density by 10,000 reviews posted in a 1,000-meter radius around the property based on a regression model. The main independent variable of interest was Airbnb density, which served as a proxy for Airbnb activity. Merante & Mertens Horn (2016) also used Airbnb density when studying the effect of Airbnb on the renting prices in Boston. They calculated Airbnb density by dividing the units listed on Airbnb by the total number of housing units in the given census tract. They found that, as suggested by reports from New York (2016) and San Francisco (Lee, 2016), Airbnb affects the long-term housing supply. Almost half of the units listed on Airbnb in Boston are offered by hosts that have multiple listings simultaneously online. These apartments are used as investment properties which leads to a decline in the supply of housing offered for the residential market in Boston. The most recent research on Airbnb is from Koster e.a. (2019). They compared areas with and without regulation on Airbnb to see if there is a difference in property price development in those areas. By using a difference-in-difference model in combination with a regression discontinuity design, they found that those areas with regulation have lower house prices and rents. What these researchers have in common is that they all use a regression model with a difference-in-difference approach and use density as a proxy for Airbnb activity. The assumption is that an increase in expected cash flow potentially has an upward effect on the valuation of the property.

Although the above researches all result in a significant price increase, the most common methodological drawback for this research approach is that density influences prices and prices influence density. The above researches do not control enough for neighborhood effect, which could play an important role in measuring the price effect of Airbnb. After all, those areas of interest to tourist might also be of interest for residents to live due to their specific qualities and characteristics. A different research method could shed new light on the debate and verify if the effect is not overestimated in previous research. The following part will, therefore, look more closely to researches that study the effect of externalities on housing prices by using a regression discontinuity model (Black, 1999; Chay & Greenstone, 2005; Sue & Wong, 2010; Aydim, 2016; Hidano & Hohsino, 2015).

Black (1999) for example used a regression discontinuity model in her research to estimate the value that parents place on the quality of schools by calculating how much more people pay for houses located in areas with better schools. Although much researchers have attempted to estimate this effect, it has always been complicated by the fact that better schools tent to be located in better neighborhoods. When there is not sufficiently controlled for neighborhood characteristics, the value of the quality of a school is overestimated. To overcome this problem, Black (1999) compared houses on opposite sides of attendance district boundaries, the geographic lines that determine which school a child attends within a school district. Because she uses school district, she can control on property tax rates and school spendings. By limiting the sample to those houses that are very close to the attendance district boundaries, she included houses within close proximity of each other but whose children attend different school. Thereby, she could control from neighborhood differences. By defining a border or sharp line it is possible to notice ‘jumps’ in test scores at attendance district boundaries, while neighborhoods continue to change in a smooth manner, thereby isolating the relationship between test scores and house prices. Her findings show that houses within 0.15 miles from the border result in a 5% increase in test scores lead to a 2.1% increase in housing prices. This amount is half the estimate of a typical hedonic housing price regression. These findings suggest that, if one does not carefully control for neighborhood characteristics, one will greatly overestimate the value of the additional school quality as measure by test scores (Black, 1999).

The research of Sue & Wong (2010) estimate the value of publicly provided local goods and services in the constituencies of the ruling party relative to those of the opposition parties in Singapore. They, like Black (1999), also used a regression discontinuity method. A simple hedonic regression tends to suffer from omitted variable bias; some factors that affect property values may be unobserved. If the omitted variables change smoothly over space, then flats that are close together are likely to share the same values for the omitted variables. Hence, to improve control for these omitted variables (locational and neighborhood characteristics), they used a regression discontinuity design. Sue & Wong found that in some case there was a moderate but highly statistically significant difference in housing prices across the electoral boundaries that separate the constituencies of the ruling party and the opposition parties.

Aydim (2016) investigates the financial aspects of energy efficiency investments in de housing market. Part of his research examined if the energy label itself directly has an additional impact on the transaction price. In order to do this het used a regression discontinuity approach based on the rule that is used to assign dwellings in energy efficiency classes. The idea behind this approach is that assignment to treatment is determined by the value of an observed characteristic begin on either side of a cutoff value. They tested if there is a discontinuity in the transaction price of the dwelling around the threshold values of EPI (+- 0.2 EPI) for different label categories. Aydim (2016) assessed if change in the energy label leads to discontinuity in the transaction price. The method of regression discontinuity allowed to plot the variation in the adjusted transaction prices based on the EPI around the cutoff points. He did not find a clear discontinuity in the transaction price of the threshold points that are used to assign dwellings in different label categories. His research concluded that there is not enough evidence to argue that the labeling itself has a significant impact on the transaction price.

Hidano & Hohsino (2015) studied the effect of seismic hazard risk information on property prices. Different to the above research they used a (two dimensional) regression discontinuity design; a design that allows them to account for neighborhood heterogeneity and locational specific effects. They created a dummy variable that equals one if the property is located in a risky zone and zero if it is not. Normally, the impact of the dummy on the house prices is estimated by regressing Y on (D,X) to construct a hedonic price function, however a RD design allows to include the risk variable. The results show that that the probability of earthquakes and of earthquake related hazards have significant negative impacts on the housing prices. Prices of residential properties in low-risk zones were between 13,970-17,380 JPY higher than those in high-risk zones depending on the type of seismic hazard risk.

If we apply this theory to the short-term rental market, we could argue that in previous research the effect of Airbnb might be overestimated because Airbnb listings are most likely located in areas that are already attractive to residents. By defining a sharp line and looking in the direct surrounding of an Airbnb listing, a regression discontinuity method could help minimize this omitted bias. Regression discontinuity uses a different assumption and estimates a more local effect around the cutoff and is therefore suitable for this research. Before going deeper into the applied methodology, first the data used for this research is discussed.

3. Data and descriptives

This chapter discusses the datasets used for this research and gives descriptives of the individual datasets. Furthermore, it provides information on how the data is processed and new variables are created. The shortfalls of the datasets are examined in the last paragraph of this chapter.

3.1 Datasets

The analysis in this research are based on two datasets. The first dataset is gathered from Inside Airbnb. Since Airbnb does not provide any data from their website for research purposes, this is the second-best option available. Inside Airbnb provides scraped data. Data scraping is the process of importing information from a website, in this case Airbnb, into a spreadsheet. Inside Airbnb is an independent noncommercial platform that provides a set of tools and data that allows analyzing how Airbnb is used in Amsterdam. For every listing advertised in the website, there are the geographical coordinates, listings per host, nightly prices, reviews per month, room characteristics, host id and the data of first sign in. The data also provides information about the composition of listings e.g. entire house/ apartment, private rooms and shared rooms. However, since Airbnb anonymizes location information, a random error is built in. Due to this error every Airbnb listing will differ by approximately 150 meters from the actual address. Inside Airbnb scrapes the Airbnb website every month to collect information on each active listing available in Amsterdam. To construct one dataset, all datasets from the different months are merged.

The analysis includes all Airbnb listings from the moment the first listing appeared in Amsterdam in 2008 up to and including 2018. All new listings from 2019 are excluded. Inside Airbnb started scraping data from 2015 onwards for all active listings. However, because the dataset includes the date every listing is registered on Airbnb it is possible to see the activity of Airbnb in the years before 2015. This means that for the years 2008-2014 only listings are included that have been active in the years after 2014. In reality, more Airbnb listings were active, but unfortunately, no data is available of all the listings in those years. Because Inside Airbnb removes inactive listings before the data is placed online, we can assume that all listings in de dataset are active listings. Some listings do not have reviews yet, which could indicate that they are inactive. However, at the moment the data was scraped the host might not had the chance to rent the listing out yet. All other listings have shown activity in the past year and are thus assumed active.

Table 1: Descriptive statistics Airbnb listings in Amsterdam

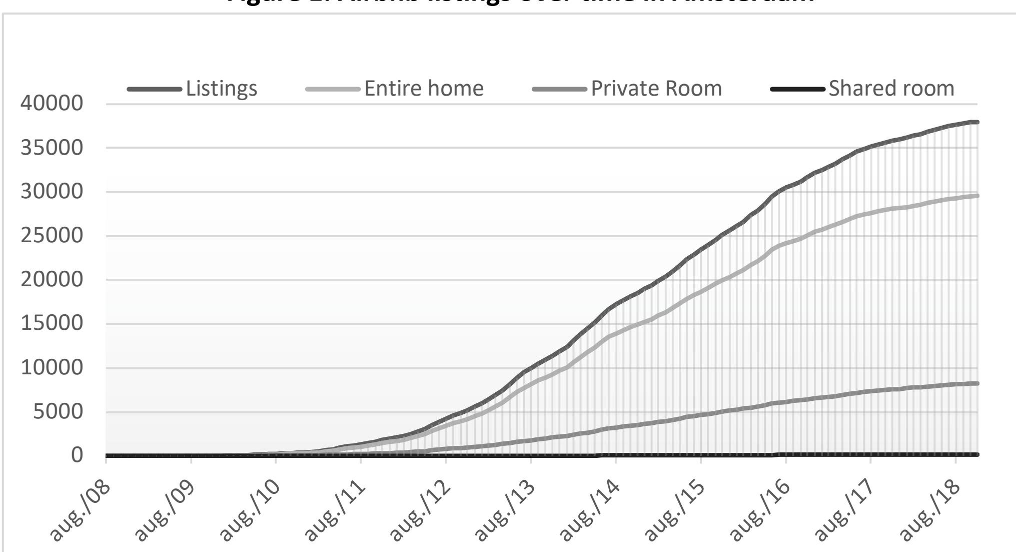
	# of obs	%
Nr. of listings	37.970	
Nr. of unique hosts	28.435	
Hosts with 1 listing	24.205	63,7%
Hosts with more than 1 listings	13.766	36,3%
Type of listing		
Entire home/apt	29.533	77,8%
Private room	8.251	21,7%
Shared room	186	0,5%

Source data: Inside Airbnb, 2018.

In total, there are 37.970 listings in Amsterdam over the period 2008-2018. These listings are placed by 28.435 unique hosts, which means that 36% of the hosts have more than 1 listing (Table 1). Since the majority of hosts have 1 listing, we can conclude that the platform is mostly used by private individuals. If we compare the current percentages of hosts with more than 1 listing with research from 2016 (Van der Bijl), it is remarkable that this percentage has increased by almost 10%. This could indicate that Airbnb more and more often is seen as a lucrative investment opportunity. When analyzing the growth of Airbnb in the past 10 years it becomes visible that the growth of Airbnb has attenuated in the past two years. For the first time since the booking platform emerged, fewer nights were booked than the year before. A decrease of 5% compared to 2017. This can partly be explained by the spreading of Airbnb to neighboring municipalities (Bakker & Kuijper, 2019). For example, in the municipalities around Amsterdam Airbnb increased by 36%. Another explanation for the declining growth is the emergence of other new short-term rental platforms that gained more market share in the past years.

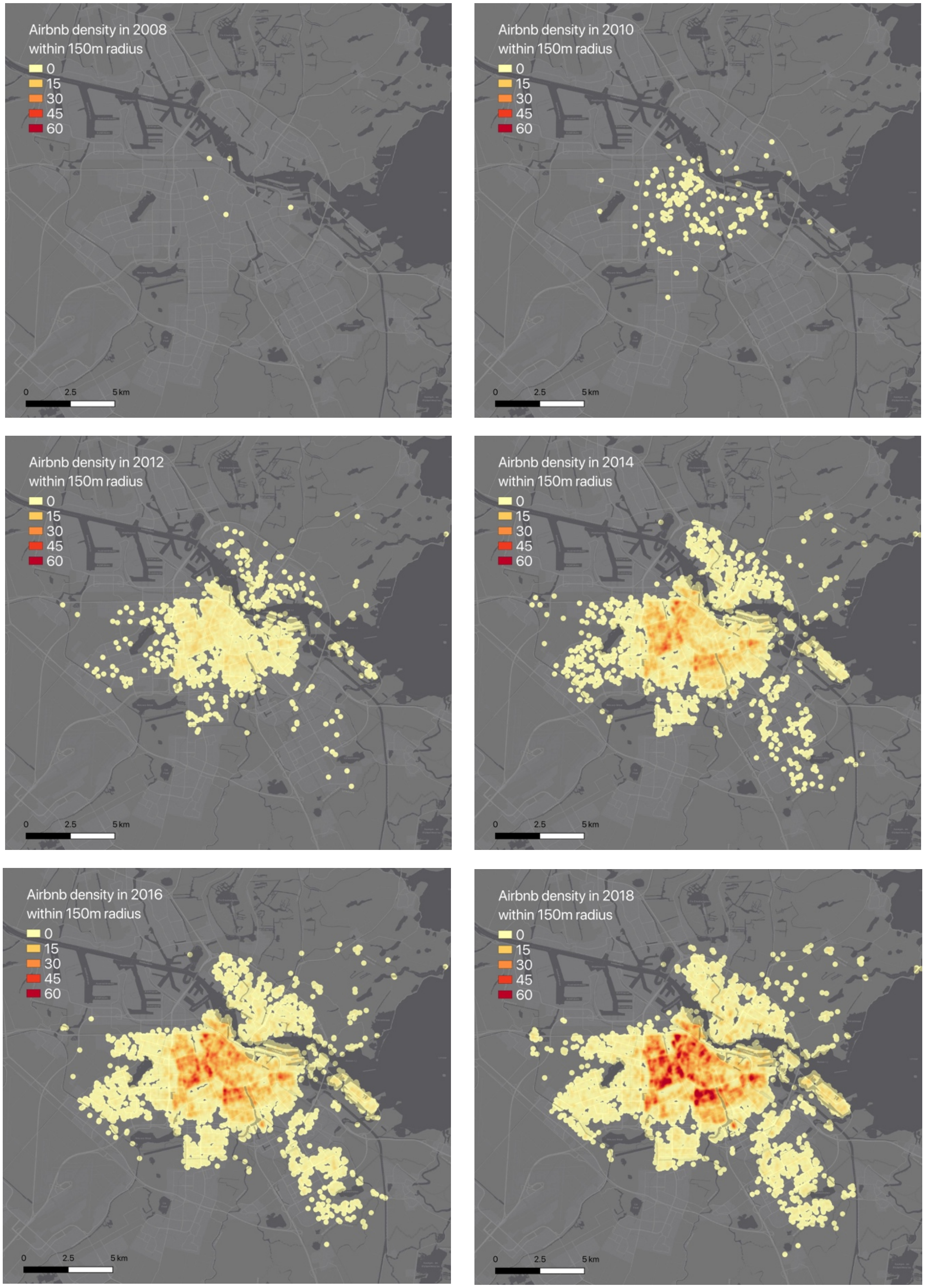
When analyzing the distribution of listing types i.e. entire home/apt or private rooms it is noteworthy that 78% Airbnb hosts rent out an entire home. Figure 1 shows the Airbnb listings from 2008 till 2018 that entered the market. The Figure also includes the amount of entire homes and private rooms. Clearly most of the Airbnb host rent out an entire home/ apt.

Figure 1: Airbnb listings over time in Amsterdam



Source data: Inside Airbnb, 2018.

Figure 2: Airbnb density within a 150m radius.



Source data: Inside Airbnb, 2018.

Figure 2 shows the density change over time of Airbnb in Amsterdam. Around every Airbnb listing a 150-meter circle is drawn. Clearly Airbnb has spread all over Amsterdam, even to the areas outside the center of Amsterdam and to Amsterdam North. In 2018 the highest density of Airbnb is concentrated within the ring of Amsterdam, but outside the Singelgracht. Most popular neighborhoods for Airbnb are De Pijp, Oud West and Baarsjes, which are also popular tourist areas. The highest amount of Airbnb's in this area is 89 Airbnb's within a 150m radius. The city center, an important tourist area for Amsterdam, surprisingly does not have the highest Airbnb density. This can be explained by the fact that this area contains a lot of canal houses that are mostly owned by companies and very wealthy citizens that most likely do not make use of Airbnb. Airbnb listings in that area can be found around main tourist attractions such as the red-light district and along main transport roads from the central station into the city.

The second data set used for this research is a housing price database from the NVM. NVM is a Dutch branch organization of real estate agents. The NVM database covers 75% of all real estate transactions in the Netherlands, and 95% of all the transactions of Amsterdam. The dataset consists of 130,421 transactions in the period between 2000 and 2018. The first year Airbnb arrived in the Netherlands was 2008 so the years 2000 till 2007 function as control observations to see if differences emerged in prices after Airbnb's started to appear in Amsterdam. For each transactions a variety of variables are given such as the transaction price, month and year, the asking price, type of property and characteristics of the property i.e. the size of the property, amount of rooms and construction year. For each transaction, the dataset provides RD coordinates with the exact location. Those transactions without RD coordinates are dropped (20,242) because it is not possible to join them with the Airbnb data. Those observations without PC4 coordinates are also dropped, which are another 308 observations. Based on an analysis of potential outliers (scatterplot) 166 observations were dropped that had sales prices below € 50,000 or above € 700,000. Observations with 0 rooms or more than 20 rooms are dropped (697) even as the observations without a building period (19 observations). Last, irrational values such as a surface of 99,999 m2 or smaller than 10 meters are dropped (31 observations). In total 103,268 observations are remaining and included in the research.

Table 2 shows the descriptive statistics of the housing transaction data. Besides the independent variable of interest also control variables are included. The dummies garden, parking, monument equal 1 if it is applicable on the transaction and 0 if it was not applicable. For the maintenance dummies 1 equals good maintenance and 0 no maintenance at all. Housing type is categorized into four classifications; apartment, detached, semi-detached and terraced. Remarkable is that 88% of the houses are apartments. The average house in Amsterdam in this dataset costs around € 261,036 in the period between 2008-2018.

Besides control variables also three Airbnb dummies are included in Table 2 for both the distances 150- and 500-meter; *Close to Airbnb*, *ln_dst_border_Airbnb* and the interaction variable *Delta dummy*. In order to create these variables, the two datasets of the housing transactions and the Airbnb datasets were aggregated into one dataset by using QGIS and STATA. Because both datasets consist of RD coordinates, it was possible to plot them on a map of Amsterdam. After the datasets were plotted on the map, they were divided into years ranging from 2008 till 2018. Per year, around every Airbnb location a buffer of 150-/500-meter is placed. This distance was chosen because it represents the direct area around Airbnb. Based on these steps it became possible to geographically join the two datasets into one.

The three variables that were created are needed to build a regression discontinuity model. First of all, the dummy variable named *CloseAirbnb* is generated, which is also the main independent variable of interest in this research. For this variable every transaction in Amsterdam either got the value 1 if it lay within the buffer of 150-/500-meter of an Airbnb listing or 0 if it was located outside that area. The second variable that was created is a log variable named *ln_dst_border_Airbnb*, which measures the distance from the edge of the Airbnb buffer to every transaction in the database. In order to generate this variable, the absolute distance from every transaction to the nearest Airbnb was measured in QGIS. In STATA the distance is adjusted by subtracting the 150-/500-meter buffer zone. These absolute results were then transformed into a logarithm. The third variable, *Delta_Dummy,* multiplies the two previous variables *CloseAirbnb* * *ln_dst_border_Airbnb* and measures the interaction between the two variables. The latter two variables initially consisted of 64,637 observation because only those transactions were included from the years that Airbnb has been active (Airbnb emerged in 2008). However, to measure the effect over a ten-year period of time, including the effect of the first listing of Airbnb in Amsterdam, it was necessary to give all housing transactions between 2000 and 2008 the value 0 in the variables *CloseAirbnb* and *ln_dst_border_Airbnb*. This resulted in a total of 103.268 observations.

In Table 1 and 2 in the Appendix A, comparison descriptives are given on the different variables inside and outside the 150-/ 500-meter buffer for the period that Airbnb was active (2008-2018) in order to analyze for differences. Comparing the two groups confirms that in those places where Airbnb is present houses are more expensive than in the area outside the Airbnb buffer. On average the square meter price is, with an € 800 difference, substantially higher in those areas within the Airbnb buffer than outside. Analyzing the prices of the rooms shows that there is very little difference between room prices of Airbnb inside and outside the buffer. Only in the 500m buffer comparison a €4 difference is visible. Because Amsterdam is a relatively small city compared to other world cities, this is not surprising. From almost all neighborhoods the city center is relatively close by. Houses inside the Airbnb area are slightly smaller, possible because they are more centrally located in Amsterdam. More than 90% of the sold houses in the buffer area are apartments versus a small 84% outside the buffer. Remarkable is that by far most transactions have been near an Airbnb which means that, in line with Figure 1, Airbnb more or less has spread over all over the city.

Table 2: Descriptive statistics of housing transaction in Amsterdam (2000-2018)

Variable	Mean	Median	Std. Dev	Min	Max	Obs.
Transaction price in €	261,036	227,000	122,385	51,050	699,100	103,268
Transaction price in € per m2	3,332	3,165	1,200	720	13,382	103,268
Close to Airbnb 150m	0.442	0.000	0.497	0	1.000	103,268
Distance to border Airbnb 150m in m2	284	86	857	0	8693	103,268
Delta dummy 150	2.027	0	2.313	-3.638	5.010	103,268
Close to Airbnb 500m	0.514	1.000	0.500	0	1.000	103,268
Distance to border Airbnb 500m in m2	406	384	772	0	8343	103,268
Delta dummy 500	3.082	4.783	3.015	-2.502	6.214	103,268
House size	4.326	4.317	0.362	2.565	6.087	103,268
Number of rooms	3.129	3.000	1.088	1.000	16.000	103,268
Apartment	0.876	1.000				103,268
Detached	0.006	0.000				103,268
Semi-detached	0.032	0.000				103,268
Terraced	0.086	0.000				103,268
Garden	0.255	0.000	0.436			103,268
Maintenance inside good	0.922	1.000	0.267			103,268
Maintenance outside good	0.979	1.000	0.143			103,268
Monument	0.023	0.000	0.151			103,268
Parking	0.100	0.000	0.300			103,268
Construction year < 1906	0.136	0.000				103,268
Construction year 1906-1930	0.278	0.000				103,268
Construction year 1931-1944	0.093	0.000				103,268
Construction year 1945-1959	0.051	0.000				103,268
Construction year 1960-1970	0.102	0.000				103,268
Construction year 1971-1980	0.042	0.000				103,268
Construction year 1981-1990	0.111	0.000				103,268
Construction year 1991-2000	0.125	0.000				103,268
Construction year > 2001	0.063	0.000				103,268
Year of transaction	2010	2010		2000	2018	103,268

Note: The NVM database covers 75% of all real estate transactions in the Netherlands, and 95% of all the transactions of Amsterdam.

3.2 Shortfalls

Although the two datasets provide a solid ground for this research, it is important to understand the shortfalls of the datasets before continuing with the methodology and results. First, Airbnb is not the only short-term rental platform on the market. As mentioned before other platforms are active as well that have a certain share of the short-term rental market. Especially in the past years, this share has increased. The outcomes of this research might be stronger and more significant if datasets from other platforms were included in the research. After all, more short-term rentals could mean a higher significant effect. Unfortunately, it was not possible to gather data from these other platforms. Since Airbnb still has the biggest market share in the short-term rental market, it is not a problem for this research. The second possible shortfall of the Airbnb dataset is that it does not originate from the company Airbnb itself, but from a non-commercial scraped website called Inside Airbnb. Nevertheless, because Airbnb does not publicize their data, this is the best option at hand and acceptable for this research. The third issue is the measurement error in the Airbnb listings location. As mentioned before, Airbnb protects the GPS location of all the listings on Airbnb by applying a random error of 150m to every listing on their website. Because these errors are applied randomly, there is no need for a correction.

The fourth constraint of the dataset is that if a property of an Airbnb host is sold and the new owner also decides to use it for short-term rental, the listing is counted twice while it is the same house that is used for Airbnb. It would appear as if more houses are subtracted from the market then there actually are. Because the precise location is not given, it is not possible to correct for this shortfall. Besides this, there may be owners who make their property available on Airbnb very rarely, and our assumption that these units influence the local housing prices may be overestimate the actual number of Airbnb properties. The last shortfall of the Airbnb data set is that the range of listings per host varies between 1 and 249 with an average of nine listings per host. This, however, might not be accurate as some host commercially manage and offer apartments for investors while they do not own the apartments themselves. This could distort the results.

3.3 Data validity

Before the regression model was executed the model was checked for multicollinearity. Multicollinearity is a phenomenon where two or more explanatory variables in a multiple regression model are highly linearly related. A method to check for multicollinearity is a correlation matrix. A correlation matrix shows the correlation coefficients between different variables included in the model. A correlation of 1 means a perfect correlation of two independent variable which implies that one variable can be explained by another variable. It is common to exclude one of the two variables from the model when a correlation of more than -0.7 and 0.7 is found. In Appendix A3 a correlation matrix is included for the independent variables of this research. The results show that the variables number of rooms and house size correspond with a correlation coefficient of 0.725 which indicates a high level of multicollinearity. Therefore, the variable number of rooms is excluded from the regression model.

4. Methodology

In this part of the research the applied research methods will be discussed. This aim of this research is to estimate the impact of Airbnb on housing prices in Amsterdam. The theoretical framework taught us that in empirical research on the effect of Airbnb on the housing market, typically hedonics regression models are used to compare the predictive effect of externalities on prices while controlling for a variety of unit characteristics. Different types of hedonic regression models exist. Most researchers that measured the effect of Airbnb used a difference-in-difference approach. A difference-in-difference is a more general before and after analysis where they used density to measure the impact of Airbnb. However, his research will use a sharp regression discontinuity model in line with the research of Black (1999) in order to take into account (unobserved) neighborhood effects more precisely while measuring the effect of Airbnb on the housing prices.

4.1 Hedonic regression model

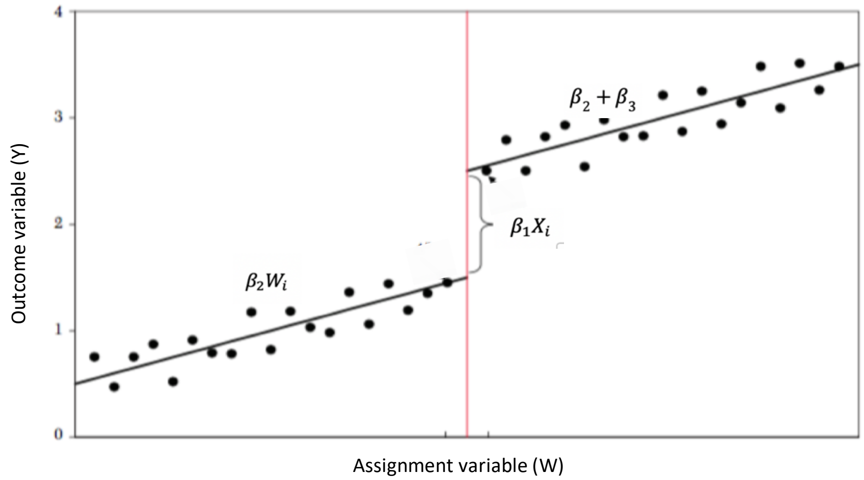
In general, hedonic regression models are used to measure the effect of multiple variables on the housing prices. A regression model is based on the equilibrium theory, a theory that assumes that housing supply is inelastic; it takes a long period of time before new houses are constructed. The theory assumes that consumers with identical preferences and income can achieve the same level of satisfaction when buying a house. Higher prices result in greater comforts and amenities. Basically, the theory assumes that the price you pay for a house is the result of the characteristics of the house and its location, and the price that is associated with each characteristic represents that of an average buyer (Black, 1999).

Unfortunately, the drawback of this basic regression model is that not all relevant house or neighborhood characteristics can be observed. This leads to omitted variables bias. For example, prices might be influenced by the fact that a specific neighborhood is more expensive than another due to certain characteristics that are unobservable with the PC4 code. In that case it is not Airbnb that drives up the prices, but other (unobserved) neighborhood characteristics that lead to higher demand and thus higher prices. The study from Black (1999) provides the methodology needed in order to estimate the effect of Airbnb on the housing prices and minimizes such problems. The methodology applied in this research used a set of dummies to take into account this more local effect. In this research the sharp regression discontinuity design is used to measures the effect of Airbnb on the housing prices. In a sharp regression discontinuity design (RDD), receipt of treatment, is entirely determined by whether variable X exceeds a defined threshold value, in this case whether or not a transaction lies within a certain distance of an Airbnb. An RDD has the following basic model:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 W_i + \beta_3 (X_i * W_i) + \varepsilon_i \qquad (1)$$

Figure 3 visualized this formula where β_1 is the main parameter of interest. β_2 and β_3 are control variables that captures the potential difference in slopes around the border.

Figure 3: Sharp regression discontinuity model



Source: Stock & Watson, 2015.

On the base of the RD comparison, the hedonic model for this research will look as follows:

$$(2) \qquad \log Pit = \beta_0 + \beta_1 CloseAirbnb_{it} + \beta_2 \log Dst\_border\_Airbnb_{it} + \beta_3 Delta\_Dummy + \beta_4 Controls_{it} + \propto_i + \delta_i + \varepsilon_{it}$$

Here the dependent variable is $\log Pit$ is the natural logarithm of the house transaction price of property i in year t. β_1 captures the regression discontinuity in levels. As described in Chapter 3, three new variables were generated; *CloseAirbnb, ln_Dst_border_Airbnb* and *Delta_Dummy,* which are based on the two datasets used for this research. The main variable of interest is *CloseAirbnb*. For this variable every transaction in Amsterdam either got the value 1 if it lay within the buffer of 150-/500-meter of an Airbnb listing or 0 if it was located outside that area. The *CloseAirbnb* variable is represented by the red line in Figure 3 and is referred to as the cutoff point. Left from the cutoff point represents the control group, in this case the transactions outside the 150-meter buffer. The skewness visualizes the percentual change in transaction prices the further you move away from the cutoff point. The right side of the cutoff point represents the treatment group. The treatment group are the transaction that lay within the 150-meter buffer of an Airbnb listing. It visualizes the interaction variable Delta_Dummy and shows if the average effect is similar for both the control- and treatment group. Also, three types of control variables are included for the transaction prices. House characteristics can influence transaction prices. Therefore, property characteristics are included in the model by $Controls_{it}$. Dummies are created for the following housing characteristics; garden, parking, maintenance inside and outside, monumental properties and construction year. Besides those characteristics also housing size and number of rooms are included. β_4 measures the effect of these characteristics on the housing price. Besides the house characteristics, it is also important to control for time δ_i and location fixed $\propto_i$ effects. Therefore, PC4 zip codes and different transaction year dummies are included. An error term ε_{it} is included. Standard errors are clustered at the PC4 zip code level to calculate serial correlation and heteroskedasticity robust standard errors.

5. Results

This chapter has the following structure. First of all, a baseline regression is done for the period of 2000-2018 whereby is controlled for time fixed effect such as economic trends, value development on the housing market and location fixed effects. By including the years before Airbnb was introduced, it is possible to measure the impact of the introduction of Airbnb on the housing market. The aim is to see if there is a 'sudden' jump in prices after Airbnb emerged on the market. After this, more closely will be looked to the period from 2008 till 2018 when Airbnb was present in Amsterdam. A baseline regression of only those years will give more insight in the effect of Airbnb on the housing market over that period of time. In this regression only relevant transactions are included which are 64,467 observations of the years that Airbnb was active. The third part of the results zooms in to the individual years Airbnb was present in Amsterdam. The differences between years will give insight in how the effect of Airbnb changes over time and whether or not it increased and becomes stronger. The above regressions are done for the 150-meter buffer. As a robustness check, all the above steps are applied on the data of the 500-meter buffer to see if the results are different.

5.1 The effect of Airbnb on the property prices in Amsterdam

In Table 3 the results of the baseline regression of the effect of Airbnb on the housing are shown. As is explained in the chapter Methodology the dependent variable is the natural logarithm of the house prices and the main independent variable of interest is the variable '*Close to Airbnb*'. Column 1 represents the effect of Airbnb on the transaction prices within a 150m radius without taking into account control variables. The results point towards a significant increase of 19% in the transaction price of houses within a 150m radius of any Airbnb. However, the R-squared of 0.048 indicates that only 4.8% of the variation in transaction price can be explained by the variable *Close to Airbnb*.

In Column 2 the housing characteristics are included in the model to control for the different characteristics of a house and their influence on the price. Hence, column 2 presents the effect of Airbnb on the transaction prices within a 150m radius including house characteristics. Results show a negative but significant effect of 30.2% lower property prices. He previous found increase is most likely due to omitted variable bias. Adding the housing characteristics increases the R-squared to 63%, which indicates a better fit than the results of column 1. All housing characteristics are significant at a 1% level. Most housing characteristics have a positive effect on the housing price; House size has a coefficient of 0.854 which indicates that a 1% increase in house size results, on average, in a 0.9% increase in house price. Besides house size also the variables garden, maintenance (inside and outside), parking and whether or not the property is a monument have a positive effect on the housing prices respectively with coefficient of 0.050, 0.098, 0.062, 0.052 and 0.129. Remarkable is that none of the building periods seem to have a positive effect on the property prices. For the house type only three categories are included because of the dummy variable trap; possible the attributes are highly correlated and can cause (perfect) multicollinearity. Therefore, the house type 'detached' is left out of the regression. House type has a positive and significant effect on property prices except for apartments. Apartments tend to be negative because on average they have a lower price than the other housing types.

In column 3, besides controlling for housing characteristics also year fixed effects are added to the model in order to account for yearly changes in the house prices in Amsterdam. In addition to this also location fixed effects are added to account for spatial correlations (PC4 fixed effects). The results estimate a 14.7% decrease of transaction prices within a radius of 150 meter around an Airbnb, with a 1% significant level. This outcome has a high R-squared of 89% which indicates that 89% of the outcome can be explained by the variables in the model. The results indicate that there was no sudden jump in prices since Airbnb became present in the city. This can be explained by the fact that Airbnb developed gradually over time. In 2008 only a few Airbnb listings were present while in the period between 2013 till 2015 the amount of Airbnb listings started to grow spectacularly. Due to this gradual growth of Airbnb listings, no sudden jump in prices is notable.

Table 3: Baseline results for housing prices in Amsterdam (150m radius)

	(1)	(2)	(3)	(4)
	Basic 2008 - 2018	Housing characteristics 2000-2018	Fixed effects 2000 - 2018	Fixed effects 2008 - 2018
Close to Airbnb 150m	0.190***	-0.302***	-0.147***	0.036***
	(0.003)	(0.014)	(0.008)	(0.007)
Distance to Airbnb buffer 150m		0.018***	0.001	0.021***
		(0.000)	(0.001)	(0.001)
Delta dummy 150		0.109***	0.045***	-0.010***
		(0.003)	(0.002)	(0.002)
House size (ln)		0.854***	0.782***	0.775***
		(0.003)	(0.002)	(0.002)
Apartment		-0.013***	-0.060***	-0.060***
		(0.005)	(0.003)	(0.005)
Semi-detached		0.242***	0.271***	0.244***
		(0.013)	(0.012)	(0.015)
Terraced		0.109***	-0.129***	-0.138***
		(0.005)	(0.004)	(0.005)
Garden		0.050***	0.060***	0.061***
		(0.002)	(0.001)	(0.002)
Maintenance inside good		0.098***	0.107***	0.109***
		(0.003)	(0.002)	(0.002)
Maintenance outside good		0.062***	0.066***	0.053***
		(0.006)	(0.004)	(0.005)
Monument		0.129***	0.055***	0.051***
		(0.005)	(0.004)	(0.004)
Parking		0.052***	0.070***	0.049***
		(0.003)	(0.002)	(0.003)
Construction year 1906-1930		-0.119***	-0.040***	-0.040***

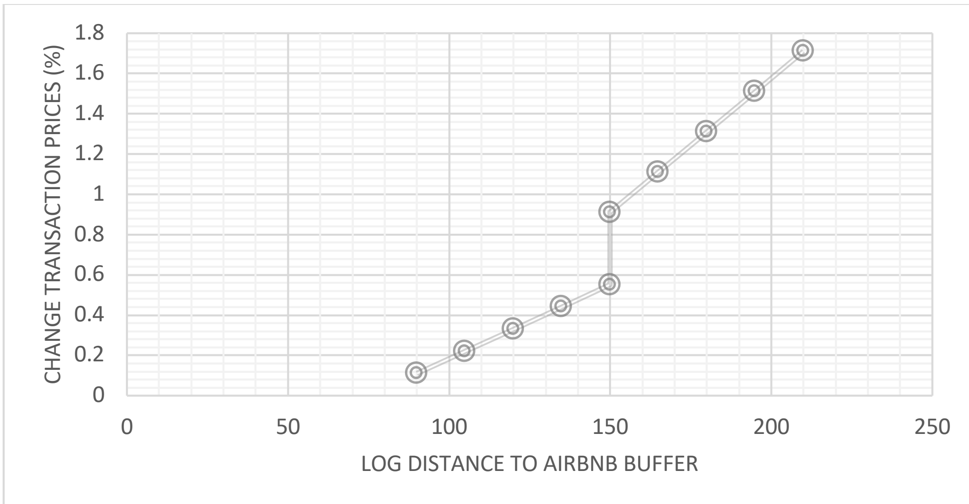
		(0.002)	(0.002)	(0.002)
Construction year 1931-1944		-0.177***	-0.041***	-0.037***
		(0.003)	(0.002)	(0.003)
Construction year 1945-1959		-0.358***	-0.126***	-0.130***
		(0.004)	(0.003)	(0.004)
Construction year 1960-1970		-0.478***	-0.191***	-0.209***
		(0.003)	(0.003)	(0.004)
Construction year 1971-1980		-0.547***	-0.161***	-0.188***
		(0.005)	(0.004)	(0.004)
Construction year 1981-1990		-0.404***	-0.111***	-0.129***
		(0.003)	(0.002)	(0.003)
Construction year 1991-2000		-0.227***	-0.020***	-0.044***
		(0.003)	(0.002)	(0.003)
Construction year > 2001		-0.230***	-0.022***	-0.025***
		(0.005)	(0.003)	(0.003)
Observations	103,268	103,259	103,259	64,467
R-squared	0.048	0.663	0.885	0.891
Housing characteristics	No	yes	yes	yes
PC4 fixed effects	No	no	yes	yes
Year fixed effects	No	no	yes	yes

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

When zoomed in to the period 2008-2018 what becomes visible is that Airbnb has a *positive*- and on the 1% level significant effect on the housing prices. The baseline results estimate an increase of 3.6% in prices of properties sold within a 150-meter radius of an Airbnb listing. Relative to the average property price, this is an increase of property prices by €9.397. All control variables are included in the model. With an R-squared of 89% the model sufficiently includes the right variables for the outcome to be valid. While the period 2000-2008 also picks up this first introduction of an Airbnb listing on the market, the period 2008-2018 only measures the variation of Airbnb listings. The sign change could be explained by the fact that Airbnb in the begin period had a negative effect on the housing market (Figure 5).

The results of the regression discontinuity model are visualized in Figure 4. The graph shows that on the 150-meter border the property prices make a 'jump' of 3.6% in price. The *Distance_border_Airbnb dummy* demonstrates that if you move away from the buffer, prices increase by 0.021% per meter. The interaction variable *Delta_Dummy* indicates if the average effect is similar for the group inside and outside the 150-meter buffer. The results show that if transaction inside the buffer get closer to the Airbnb listing, a 0.021 - 0.01 = 0.011 % decrease in transaction price is estimated. On average, the effect of distance to the buffer is negative for transactions inside the buffer in comparison with transactions outside the buffer. However, these values are very low.

Figure 4: Visualization results regression discontinuity model



Because of the positive and significant effect of Airbnb listings on the housing prices in the period 2008-2018 it is interesting to zoom in to the individual years that Airbnb has been present in Amsterdam. Figure 5 visualizes the results of the regression per year. Remarkable is that is the first years mostly there is no or a negative effect of Airbnb listings on the housing market. However, from 2014 when Airbnb substantial started to grow the results estimate a yearly increasing, positive effect of Airbnb on the property prices within a 150-meter of an Airbnb listing. This suggest that as the density increases the effect on the property prices increases as well. The visualization of Airbnb density is presented in Figure 6 and illustrates the increase in Airbnb listings per km2 in Amsterdam over time. Figure 5 and Figure 6 indicate that when density increases, the effect of Airbnb on the property prices increases significantly as well. Interestingly, the average density is not so high that the effect turns negative again. These results do suggest, from a policy perspective, that a relatively small amount of Airbnb listings most likely does not have a large impact on the housing market. A small number of Airbnb listings would keep Amsterdam more accessible for outsiders, i.e. houseowners outside the city and tourists. Interestingly, the density has not been high enough to cause a turning point in the effect yet. For policy makers a tradeoff is needed between facilitating tourism accommodation on the one hand and keeping the city accessible for outsiders on the other hand. Density can be used as a tool to balance them out.

Figure 5: The effect of Airbnb on the housing prices per year (2008-2018).

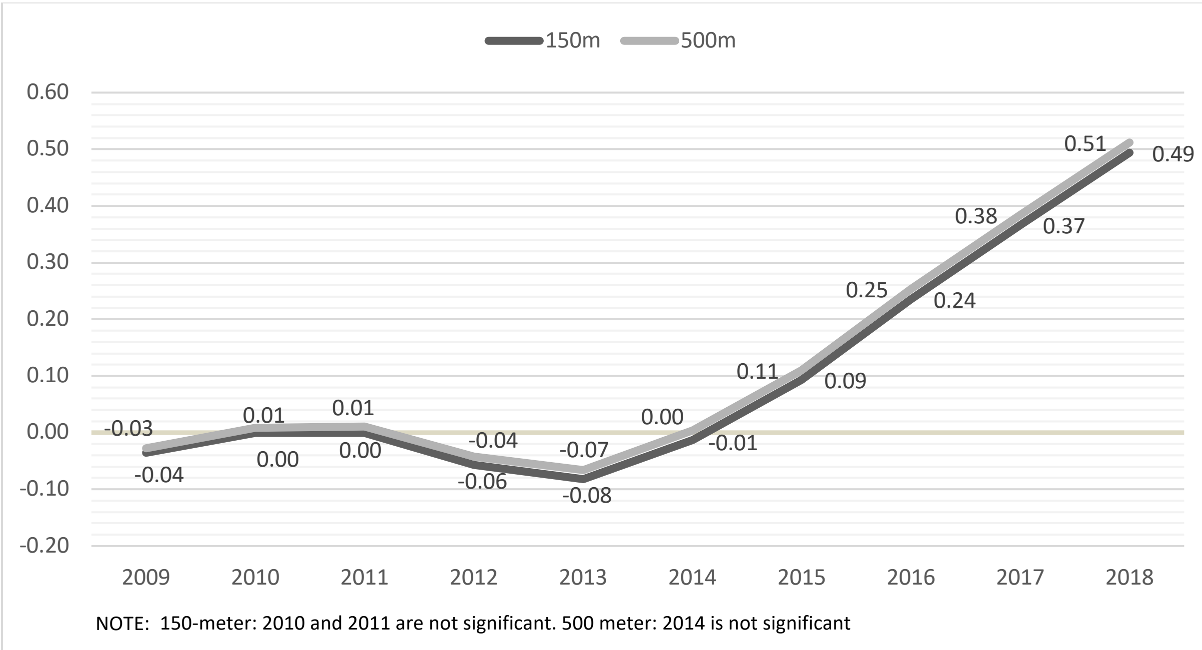
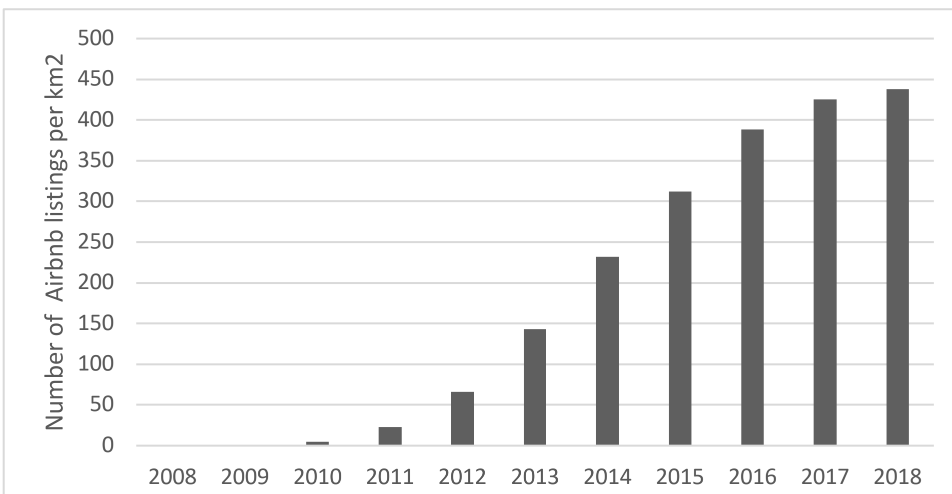


Figure 6: Density of Airbnb per km2 in Amsterdam (2008-2018).



Koster e.a. (2019) found in their research that ordinances in certain areas in Los Angeles result in a decrease in housing prices of 3%. In Los Angeles the government applied ordinances in specific areas, often those that are attractive to tourists. Because of these ordinances they were able to measure the price differences in areas where Airbnb was present and where it was not allowed. In Amsterdam such regulations are not applicable which is why this research used a different approach with a 150 buffer around every Airbnb listing. Regardless of this difference, the results of the research of Koster e.a. (2019) are quite similar to the findings in this research. They found a 3% decrease in areas where Airbnb is not present, while this research found a 3.6% increase of property prices in areas where Airbnb is present. Also, the findings of this research are in line with the researchers mentioned in the theoretical framework who found an increase in housing prices.

As a robustness check also the above steps are carried out for the 500-meter buffer. The results can be found in Appendix A4. For the period 2008-2016 estimates show a 10.6% increase of the housing prices within 500-meters of an Airbnb listing, with a 1% level significance. This increase seems quite a lot. Because Amsterdam is a fairly small city a 500-meter radius might be too big of a radius to properly measure the effect.

6. Limitations and future research

In this section of the research the limitations of this study are discussed. Additionally, some suggestions are provided on future research opportunities.

The research on the effect of Airbnb on the property prices could be improved in a couple of ways. First of all, a more accurate distance could be used to measure the effect. The distances in this research are chosen because 150- and 500-meter represent the direct surrounding of an Airbnb. However, a more advanced Stata user could generate the optimum distance for the regression discontinuity model. It could be interesting to know at what distance of an Airbnb listing the biggest price jump is noticeable. Secondly, the research could focus specifically on tourist areas compared to non-touristic areas. By zooming in to certain areas where Airbnb is mostly present, such as tourist areas, a different result could be found. Airbnb might influence prices in those areas while not affecting the housing prices in places with less demand. This research methodology could be used, although some areas need to be excluded from the research. Third, this research could improve significantly if data from the company Airbnb was provided instead of the data from Inside Airbnb. The exact address of the listings could strengthen the outcomes of this research. This would enable researchers to compare price developments of similar houses that do and do not use Airbnb. Fourth, this research could also improve if renting transaction prices were included as well. Renting prices could be analyzed in a similar way, by using a regression discontinuity model. Comparing the results gives a more complete overview of the effect of Airbnb on the housing market in Amsterdam in general. Fifth, it would be good to make a distinction between entire homes and rooms in the regression. The two types of Airbnb listings could indicate a significantly different effect on the property prices. One could argue that mostly the entire apartments subtract houses from the market and thereby drive up the housing prices. Rooms and entire apartments could have a different effect on the housing prices. Also, in addition to this research the time on the market could be analyzed to see if houses are shorter periods on the market due to the higher demand. This could also explain higher prices in the market. This additional analysis could strengthen the findings in this research. Besides this, the research could also include both the asking price and selling price.

With regards to future research, it would be interesting to find out what segment of the housing market is mostly used for Airbnb. The results of this research showed that Airbnb is less dense in areas with very expensive houses. Amsterdam is mostly short of houses in the low and middle segment of the market and therefore becomes unaffordable for many people. It is those people that will also use the opportunity of Airbnb to generate extra income to afford living in the city. Certainly, the segment of the market where Airbnb is used commonly, will therefore experience the highest price increase as well, due to both the shortage of that segment on the market and the extra income generating possibility. Also, it could be interesting to do more research to the effect of legislation on the housing prices. Only two years ago, the municipality of Amsterdam implemented new regulation. Soon it will be possible to see if the regulation has been effective. It would be wise to not only include Airbnb, but other short-term rental platforms as well. Their market share is increasing while Airbnb for the first year showed a decrease in their growth. For policy makers it would be valuable to see which regulations are effective and which are not. Because many cities are implementing different types of laws and regulations comparison between different regulation would be of great value.

7. Conclusion

Affordable housing and housing shortage have become a major issue in several world cities. Many politicians accuse platforms like Airbnb for putting pressure on the already overheated housing market. The short-term rental platform Airbnb, that had an enormous growth in the past ten years, has become the main topic in contemporary debates on affordable housing. Opponents of the short-term rental market argue that Airbnb increases both housing- and renting prices and, because many apartments are permanently used as tourist accommodation, reduce the supply of properties for residential purposes. In addition, Airbnb is also blamed for causing other externalities such as noise, nuisance, increased traffic, parking- and waste management issues and increased crime in areas where Airbnb is present (Merante & Horn, 2016; Sheppard & Udell, 2016; Barron e.a., 2018). Proponents on the other hand argue that Airbnb provides residents with an extra income stream that benefits the local economy. Moreover, those who rent out a spare room or supply their entire home during temporary absences, provide extra rooms to accommodate the increasing demand from tourists. Their housing capacity would otherwise be underutilized (Gurran & Phibbs, 2017).

Researchers who studied the effect of Airbnb on the housing prices all found a positive effect, meaning that Airbnb affects the housing prices in an upward direction; prices tend to be higher in those places with a high density of Airbnb. Most of these researchers use density of Airbnb in a difference-in-difference model to measure this effect. However, research of Black (1999) concluded that such an approach does not control enough for unobserved neighborhood effects. Those areas attractive to tourist, might also be of interest to permanent residents because of the neighborhood specific characteristics. In that case, price increase might also be caused by a high demand in general. Airbnb alone cannot be blamed for this, which could mean that the effect of Airbnb on the housing prices is overestimated. Black (1999) takes care of this problem in her research by using a regression discontinuity model. In the case of Airbnb, a regression discontinuity approach gave new insight in the effect of Airbnb on the property prices. The model is based on two groups: a treatment group of transactions that has an Airbnb within a radius of 150-meters and a control group that does not have an Airbnb nearby.

A baseline regression is done for the period of 2000-2018 whereby is controlled for time- and location fixed effects. By including the years before Airbnb was introduced, it became possible to measure the impact of the introduction of Airbnb on the housing market. The results estimate a 14.7% decrease of transaction prices within a radius of 150 meter around an Airbnb, with a 1% significance level. The results indicate that there was no sudden jump in prices since Airbnb became present in the city. This can be explained by the fact that Airbnb emerged gradually over time. The regression for the period 2008-2018 indicates that Airbnb has a *positive*- and on the 1% level significant effect on the housing prices. The baseline results estimate an increase of 3.6% in prices of properties sold within a 150-meter radius of an Airbnb listing. While the period 2000-2008 picks up this first introduction of an Airbnb listing on the market, the period 2008-2018 only measured the variation of Airbnb listings. The sign change can be explained by the fact that Airbnb in the begin period had a negative effect on the housing market. This also becomes visible in the last regression of this research, which zooms in to the individual years Airbnb was present in Amsterdam. The differences between years gave insight in how the effect of Airbnb changed over time. The results show that, for the 150-meter radius, since 2014 the effect of Airbnb has been significant and increasing fast. This indicates that as the density of Airbnb intensifies, the effect of it on the housing prices also increases.

As a robustness check, all above steps are applied on the data of the 500-meter buffer to see if the results are different. Within a 500-meter radius an increase of 10.6% of property prices is found within the period 2008-2018.

Not everyone benefits from Airbnb, clearly there are winners and loser. Homeowners and residents of Amsterdam gain personal profit from Airbnb as it increases the value of their houses to some extent and generates extra income. However, for those who would like to move to Amsterdam, supply of houses is limited, and property prices are more expensive, partly due to Airbnb. On the other hand, Airbnb is providing accommodation to facilitate the high demand from tourists in Amsterdam. To limit further pressure on the residential market, policy makers should focus on finding the equilibrium of the maximum amount of Airbnb listings in certain areas to limit the effect of increased housing prices, while still meeting demands from the tourist industry and providing them with accommodation.

Measurements could include demanding a license for home owners to attend the short-term rental market. This would allow the government to set a maximum on the amount of Airbnb listings in areas based on the number of tourists an area could bear, without pushing away local people. Such limits could be applied specifically in those areas that are in high demand by tourists. This, in combination with the current measure to limit of 30 days per year could help to reduce the effect on the property prices while still allowing tourism in the city. However, one need to make sure that measurements are equal for all residents in the city. Applying rules in certain areas could artificially create richer areas and make certain groups benefit more from short-term rental market than others. Most importantly, governments and the company Airbnb need to cooperate and work together to help address the problems emerging due to the platform. Openness from Airbnb on the Airbnb locations would allow governments to maintain policy. Until that moment, limited regulations are applicable that are strong enough to stop the short-term rental market from growing any further.

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Appendix A

Table A1: Descriptive statistics 150m buffer

	Outside 150m				Inside 150m			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Transaction price in €	247,416	114,769	61,000	699,000	289,583	130,193	55,000	699,100
Transaction price in € per m2	3,091	975	914	12,188	3,895	1,320	818	13,382
Price Airbnb per night in €	114	57	18	899	110	108	0	6,548
Distance to Airbnb buffer 150m	6.123	1.749	-6.128	9.070	4.589	0.596	-3.638	5.010
Delta dummy 150	0.000	0.000	0.000	0.000	4.589	0.596	-3.638	5.010
House size in m2	82	30	22	300	77	29	13	300
Number of rooms	3	1	1	11	3	1	1	13
Apartment	0.845				0.915			
Detached	0.007				0.004			
Semi-detached	0.040				0.021			
Terraced	0.108				0.060			
Garden	0.281	0.449	0	1.000	0.220	0.414	0	1
Maintenance inside good	0.913	0.282	0	1.000	0.926	0.261	0	1
Maintenance outside good	0.980	0.140	0	1.000	0.982	0.132	0	1
Monument	0.017	0.131	0	1.000	0.027	0.162	0	1
Parking	0.102	0.303	0	1.000	0.085	0.280	0	1
Construction year < 1906	0.122				0.155			
Construction year 1906-1930	0.269				0.290			
Construction year 1931-1944	0.083				0.105			
Construction year 1945-1959	0.053				0.049			
Construction year 1960-1970	0.112				0.089			
Construction year 1971-1980	0.050				0.032			
Construction year 1981-1990	0.118				0.102			
Construction year 1991-2000	0.153				0.089			
Construction year > 2001	0.042				0.090			
Year of transaction	2015	2	2008	2018	2015	2.192937	2008	2018
Entire apartment Airbnb	0.753	0.431	0	1	0.8119239	0.3907772	0	1
Observations	19,027				45,619			

Table A2: Descriptive statistics 500m buffer

	Outside 500m				Inside 500m			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Transaction price in €	252,444	116,245	73,000	699,000	282,558	128,966	55,000	699,100
Transaction price in € per m2	3,105	981	937	8,774	3,895	1,320	818	13,382
Price Airbnb per night in €	110	108	0	6,548	114	47	25	899
Distance to Airbnb buffer 150m	6.678	1.491	-0.988	9.029	5.995	0.463	-2.502	6.214
Delta dummy 150	0.000	0.000	0.000	0.000	5.995	0.463	-2.502	6.214
House size in m2	83	30	22	300	77	29	13	300
Number of rooms	3	1	1	10	3	1	1	13
Apartment	0.846				0.905			
Detached	0.007				0.004			
Semi-detached	0.040				0.024			
Terraced	0.107				0.067			
Garden	0.282	0.450	0	1	0.228	0.420	0	1
Maintenance inside good	0.915	0.278	0	1	0.924	0.265	0	1
Maintenance outside good	0.981	0.138	0	1	0.982	0.134	0	1
Monument	0.014	0.119	0	1	0.026	0.160	0	1
Parking	0.109	0.312	0	1	0.086	0.281	0	1
Construction year < 1906	0.124				0.148			
Construction year 1906-1930	0.268				0.288			
Construction year 1931-1944	0.084				0.100			
Construction year 1945-1959	0.051				0.050			
Construction year 1960-1970	0.109				0.095			
Construction year 1971-1980	0.050				0.034			
Construction year 1981-1990	0.115				0.108			
Construction year 1991-2000	0.160				0.091			
Construction year > 2001	0.038				0.086			
Year of transaction	2009	1.031	2008	2018	2014	2.512	2008	2018
Entire apartment Airbnb	0.749	0.434	0	1	0.805	0.397	0	1
Observations	11,563				53,083			

Table A3: Correlation matrix independent variables

	Trans-action price	Close to Airbnb 150m	Dst to border 150m	Delta dummy 150m	House size	Garden	Maintenance inside	Maintenance outside	Monument	Number of rooms	Parking
Transaction price	1										
Close to Airbnb 150m	0.2184	1									
Dst to border 150m	0.1573	0.483	1								
Delta dummy 150	0.2342	0.9852	0.5015	1							
House size	0.6215	-0.1303	-0.0974	-0.143	1						
Garden	0.1939	-0.0717	-0.0415	-0.0783	0.2884	1					
Maintenance inside	0.0927	0.0127	-0.0008	0.0156	0.0104	-0.0217	1				
Maintenance outside	0.034	0.0197	0.023	0.0208	-0.0088	-0.0271	0.3535	1			
Monument	0.1166	0.0204	-0.001	0.0231	0.0174	-0.0141	0.0085	-0.0016	1		
Number of rooms	0.4386	-0.0489	-0.0153	-0.0604	0.7245	0.2714	-0.06	-0.0358	-0.0216	1	
Parking	0.1854	-0.0427	-0.0321	-0.0478	0.3162	0.0848	0.0455	0.017	-0.0336	0.1746	1

Table A4: Baseline results for housing prices in Amsterdam (500m radius)

	(1)	(2)	(3)	(4)
	Basic 2000-2018	Housing characteristics 2000-2018	Fixed effects 2000 - 2018	Fixed effects 2008 - 2018
Close to Airbnb 500m	0.165***	-0.450***	-0.135***	0.106***
	(0.003)	(0.020)	(0.011)	(0.011)
Distance to Airbnb buffer 500m		0.017***	-0.001	0.020***
		(0.000)	(0.001)	(0.001)
Delta dummy 500		0.100***	0.024***	-0.029***
		(0.003)	(0.002)	(0.002)
House size		0.849***	0.780***	0.774***
		(0.003)	(0.002)	(0.002)
Apartment		-0.010**	-0.061***	-0.060***
		(0.005)	(0.003)	(0.005)
Semi-detached		0.238***	0.270***	0.245***
		(0.013)	(0.012)	(0.015)
Terraced		0.122***	-0.129***	-0.137***
		(0.005)	(0.004)	(0.005)
Garden		0.049***	0.060***	0.061***
		(0.002)	(0.001)	(0.002)
Maintenance inside good		0.101***	0.108***	0.109***
		(0.003)	(0.002)	(0.002)
Maintenance outside good		0.063***	0.067***	0.054***
		(0.006)	(0.004)	(0.005)
Monument		0.129***	0.055***	0.051***
		(0.005)	(0.004)	(0.004)
Parking		0.055***	0.071***	0.050***
		(0.003)	(0.002)	(0.003)
Construction year 1906-1930		-0.123***	-0.041***	-0.039***
		(0.002)	(0.002)	(0.002)
Construction year 1931-1944		-0.176***	-0.040***	-0.037***
		(0.003)	(0.002)	(0.003)
Construction year 1945-1959		-0.374***	-0.130***	-0.131***
		(0.004)	(0.003)	(0.004)
Construction year 1960-1970		-0.500***	-0.193***	-0.209***
		(0.003)	(0.003)	(0.004)
Construction year 1971-1980		-0.565***	-0.161***	-0.189***
		(0.005)	(0.004)	(0.004)
Construction year 1981-1990		-0.419***	-0.112***	-0.130***

		(0.003)	(0.002)	(0.003)
Construction year 1991-2000		-0.239***	-0.022***	-0.045***
		(0.003)	(0.002)	(0.003)
Construction year > 2001		-0.236***	-0.024***	-0.025***
		(0.005)	(0.003)	(0.003)
Observations	103,268	103,259	103,259	64,467
R-squared	0.036	0.648	0.884	0.891
Housing characteristics	No	yes	yes	yes
PC4 fixed effects	No	no	yes	yes
Year fixed effects	No	no	yes	yes

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