Economics and Business: Marketing

Erasmus School of Economics
Erasmus University Rotterdam

Master Thesis

Is Airbnb driving up house prices? A study of house transaction prices in Amsterdam.

Author: Jesse Vos (454596jv)
Coach: Dr Nuno Camacho
Co-reader: Dr Arie Barendregt
16-08-2021

Abstract

This thesis investigates the effect of Airbnb on house transaction prices in the municipality of Amsterdam. In this research, Airbnb supply is calculated by looking at the number of Airbnb listings in a specific zip code per year. House prices are measured by looking at the average transaction value per zip code per year. In this research, I find no significant relationship between Airbnb penetration - or number of Airbnb listings - and house transaction prices, when controlling for economic changes per year. Therefore, the results of this thesis are not in line with previous research investigating the effect of Airbnb activity and house transaction prices. However, this research does find that zip codes with high Airbnb penetration have decreasing house transaction prices due to government regulation. I discuss possible explanations for this discrepancy in the conclusion of my thesis.

Table of Contents

1. Introduction

The sharing economy is based on a collection of peer-to-peer (P2P) platforms, in which individuals and micro-entrepreneurs can offer temporary ownership of products and offer services to other consumers. Eckhardt, et al., (2019) define the sharing economy as a system characterized by five components: temporary access, transfer of economic value, platform mediation, expanded consumer role and crowdfunded supply. Peer-to-peer platforms differ from regular service providers and platforms in the way the offered product consumed. Unlike regular providers, peer-to-peer companies provide the opportunity to individuals to rent out their own personal assets when they are unutilized. This phenomenon is called “sharing”, or in other words “collaborative consumption” (Belk, 2010; Belk, 2014). This change has been supported by digitalization and advancements in communication systems. These innovations caused the possibility for consumers to become co-producers during the value creation process (Bloom, Garicano, Sadun, & van Reenen, 2014; Lusch & Nambisan, 2015).

The sharing economy’s ecosystem involves three main players: (1) a service provider, (2) a customer, and (3) a service enabler (or “peer-to-peer platform”). The *service provider* makes an asset available to the customer. A distinctive aspect of the sharing economy is that this asset is often a private asset and does not need to belong to a corporation. The *customer* can temporarily use this asset by paying a fee for this service. Importantly, the match between the service provider and the customer is orchestrated by the *service enabler* who facilitates the trade between both parties (Kumar, Lahiri, & Dogana, 2018). Because they typically orchestrate matches between private individuals, service enablers in the sharing economy are also known as “peer-to-peer platforms”. Peer-to-peer platforms are quite diverse and operate in many industries, such as the taxi industry (e.g. Uber and Lyft), rental accommodations (e.g. Airbnb), and food services (e.g. Deliveroo)[1].

Peer-to-peer platforms offer a unique opportunity to consumers to earn additional income by platform. Benefits of the participating as a seller on the peer-to-peer buyer are authentic experiences, the sense of a community and lower prices. However, the introduction of peer-to-peer platforms also have negative effect for competitors in the industry as well as negative externalities to stakeholders (Köbis, Soraperra, & Shalvi, 2021).

In the travel and tourism industry, Airbnb is an international peer-to-peer platform that offers individuals to rent out their property for short-term rental. Airbnb was founded in 2008 and has grown massively. The P2P-platform has become the largest home-sharing company and has over 5.6 million listings (Airbnb accommodations) worldwide. These listings are spread over more than 220 countries and 100,000 cities in the world[2]. Airbnb is therefore larger than the world's biggest traditional hotel groups such as Marriott International, Hilton Worldwide and InterContinental Hotels Group, which have approximately 1.4 million, 780 thousand, and 886 thousand rooms, respectively (Marriott International, 2020; Hilton Worldwide, 2019; InterContinental Hotel Group, 2020).

Despite its success novel business model, Airbnb is often accused of causing negative externalities towards the economic environment and social environment (e.g., gentrification of city centers and rising rental prices). For instance, prior research shows that the development of Airbnb negatively impacted the revenues of incumbent hotels. Zervas, Proserpio, & Byers (2017) found causal evidence for dropping hotel revenue in the state of Texas because of the introduction of Airbnb. The research compared the difference in hotel revenue development in cities with high Airbnb penetration and cities with relatively low Airbnb penetration. Another

[1] In the case of Airbnb, the service provider is the *host,* the customer is the *guest,* and the *service enabler* is Airbnb and its platform.
[2] https://news.airbnb.com/about-us/

study on the Austin hotel market confirmed the negative impact of Airbnb on financial performance of incumbent hotels (Xie & Kwok, 2017).

Since the seminal studies of Zervas et al. (2017) and Xie and Kwok (2017), researchers tried to generalize the negative effect of Airbnb on incumbent's hotel performance. Consistent evidence is found for ten hotel markets of 10 major US cities (Dogru, Mody, & Suess, 2019) and markets outside the United States (Dogru, Hanks, Ozdemir, et al., 2020). However, other research suggests that the impact of Airbnb on the hotel market is quite limited. A case study on the Parisian hotel market found that the competition between hotels and Airbnb is not completely direct because of different seasonality patterns and geographical locations of the hotels and Airbnb's listings (Heo, Blal, & Choib, 2019). Consequently, some scholars started searching for contingency factors that could explain in which conditions Airbnb growth impacts the performance of incumbent hotels, and in which conditions it does not. An example is Dongru, Hanks, Mody, et al. (2020), who find evidence that franchised hotels are more effected by the rise of Airbnb than chain-hotels and independent hotels.

Given the prevalent debate about the effect of Airbnb penetration on housing prices, it is surprising that most research has concentrated on the impact of Airbnb in the hotel industry, neglecting the real estate market. The goal of this thesis is to fill this gap. Closing the gap in research is quite important since Airbnb's effect on the increasing price development causes quite some social unrest in urban areas with high tourism flows. Moreover, these negative externalities and resulting social unrest have caused many city governments to regulate Airbnb in various forms (Nieuwland & van Melik, 2018), as I discuss next.

1.1. House prices and regulation

Around the world many city governmental institutions regulate Airbnb's activity. The regulations differ per city and regulations are quite diverse. Examples of regulations are a limit on the number of guests per listing, a limit on number of nights a guest can rent an Airbnb, a limit on the number of times a listing can be rented out to a guest, obedience of safety regulations, requirement of primarily residence of the owner or complete prohibition of Airbnb activity (Nieuwland & van Melik, 2018). Common reasons for regulation are negative externalities such as the treat to urban livability and increasing prices in the housing market.

Relative to the extensive research done on Airbnb's effect on incumbent's hotel performance, the research done on negative externalities towards the social environment (such as Airbnb's effect on the housing market) is quite limited. There is some evidence of negative external effects of Airbnb in the housing market. Past research has divided the housing market in two different segments, first the housing rental market and the house transaction market. Most research has been done on rental market increases due to Airbnb activity. A recent article finds evidence of rising rents due to higher Airbnb density in Boston (Horn & Merante, 2017), they concluded that a one standard deviation increases in Airbnb density caused a 0.4% increase in rental prices. Another research finds evidence of rising rental prices in the Los Angeles housing market (Lee, 2016).

Outside the United States, a research finds evidence of rising private rental rates due to Airbnb in some French cities: Lyon, Montpelier and Paris (Ayouba, Breuillé, Grivault, & Le Gallo, 2020). An extensive research finds evidence of both increasing housing prices and increasing rental rates in the United States. The research found that a one percent increase in registered Airbnb listings leads to a 0.018% increase in rental rates and a 0.026% increase in house transaction prices (Barron, Kung, & Proserpio, 2021)

This research will focus on the housing transaction market, this market consists of buyers of a house who buy the entire property and sellers who own and want to sell a property (Barron, et al., 2021). In sum, in this thesis I investigate if and to what extent house prices increase in certain neighborhoods because of the growth in Airbnb penetration in such neighborhoods. Also, important the unit of analysis in this research is the house transaction price development of residential properties, properties used for other purposes are not considered. This results in the following research question:

RQ: What is the effect of Airbnb on house transaction prices of residential properties?

The goal of this research is to close research gap of Airbnb interference in the housing market. There are three main areas in which this research tries to add knowledge. First, current knowledge on Airbnb interference on both the rental market and housing transaction market in the United States (Barron, et al., 2021; Horn & Merante, 2017; Lee, 2016; Garcia-López, Jofre-Monseny, Martínez-Mazza, & Segú, 2020; Chang, 2020). In this research, I try to find evidence in Europe and therefore try to generalize if this interference also happens outside the United States. Second, another question that remains unanswered is if government regulations on Airbnb have an effect on the house transaction price development. Third, this research tries to find causal evidence of this effect.

1.2. Academic and managerial relevance

This research is academically relevant since it tries to build on existing research on negative externalities of Airbnb and other short-term rentals (STR). Also, the existing research on Airbnb's activity on housing prices is small, therefore this research tries to build more generalizable evidence of Airbnb's effect on the housing market. By doing this research, I try build more extensive knowledge on the external effects of Airbnb on its sociological environment.

From a managerial perspective this research is important for government policy makers and other stakeholders. This research can be used as a complementary evidence for city government policy makers to justify the motivation to regulate Airbnb's activity. Since the effect of Airbnb activity on house prices is still quite limited. Therefore, justifying the regulative actions against Airbnb by city policy makers. Moreover, in this paper I also wants to find evidence that government regulation is effective in limiting the effect of Airbnb on the housing market.

1.3. Content of research

In this thesis, an overview of related research will be given. The related research will look at previous research related the correlation between house transaction prices and Airbnb activity. Also, the chapter explains how it relates to previous research regarding the effect of Airbnb on hotels. The next chapter goes into the data collection process and the different preprocessing operations, it will be followed by a descriptive analysis. Next, the methodology chapter will be introduced, followed by the results of the regression analysis. The thesis will be followed by a discussion of the results. Lastly, the limitations and future areas for research will be discussed.

2. Related Literature

The effect of home-sharing platforms (such as Airbnb) on the house price development has only got significant research attention quite recently. Lee (2016) has studied the effect of Airbnb on the rental rates of residential properties in the City of Los Angeles, and found that Airbnb decreased the rental supply, which possibly affects the rental rates. Moreover, similar research has been done on Airbnb effect of rental prices between 2016 and 2017 in Boston, Massachusetts (Horn & Merante, 2017). The research found that a standard deviation increases in listings caused a 0.4% increase in sales. Ayouba, et al. (2020) investigated the impact of Airbnb on renting prices in different French cities, the research found mixed results. Some cities showed an increase of rental prices due to Airbnb activity, while other cities do not show a correlation.

Until quite recently, there was no research regarding the effect of Airbnb on housing transaction prices, which are the final sales prices of residential houses[3]. Recent research confirmed the negative effect of Airbnb penetration on real estate prices by looking at the house transaction prices in Taiwan (Chang, 2020). Garcia-López, et al. (2020) finds causal evidence of rising transaction prices, posted prices, and rental prices in Barcelona. The paper suggest that Airbnb increases the rental prices with 1.9% and house transaction prices with 4.6%. Moreover, the same research finds that neighborhoods in the top decile of Airbnb activity distribution have an increase in house prices of 17%. Another research finds the same evidence for Airbnb activity with zip codes as unit of analysis (Barron et al., 2021). This research is different from previous research since it does not focus on a specific city, but a large area. The study looks at all zip codes within the United States and finds that a one percent increase in

[3] Note that transaction prices differ from posted prices, which are the asking prices of residential properties (which may, therefore, deviate from the final sales price).

Airbnb listings increases the house transaction prices with 0.0026%. An overview of all relevant research is given in Table 1.

Study	**Journal Published**	**Geographical market**	**Economical market**	**Unit of Analysis**	**Effect size**
(Horn & Merante, 2017)	*Journal of Housing Economics*	Boston, MA	Rental Market	Tract	0.4% increase per one-standard deviation increase of Airbnb listings
(Ayouba, et al., 2020)	*International Regional Science Review*	French cities	Rental Market	Neighborhoods	0.385% to 0.5242% increase per one-point increase of Airbnb density
(Garcia-López, et al., 2020)	*Journal of Urban Economics*	Barcelona, Spain	Rental Market House transaction market	Neighborhoods	1.9% increase in rentals and a 4.6% increase in transaction prices because of Airbnb activity
(Chang, 2020)	*Journal of Housing Economics*	Taiwan	Rental Market House transaction market	Neighborhoods	0.38%. increase per one-standard deviation increase of Airbnb listings
(Barron, et al., 2021)	*Marketing Science*	United States	Rental Market House transaction market	U.S. zip code	0.018% increase in rents and a 0.026% increase in sales price per 1% Airbnb listings increase

Table 1: Literature review of research of Airbnb on the housing market

This research is in line with past research focusing on the negative externalities of Airbnb. Despite the extensive research done on home-sharing's effect on the hotel market, other research is done on discrimination of guest in short-term rental (Edelman & Luca, 2014). However, Airbnb does show positive external effect to the overall labor employment in the hospitality industry (Dogru, Mody, et al., 2020). In general, this research does connect to other research of various effects of the sharing economy on its environment. Furthermore, the research contributes to the research of the impact of Airbnb on the hotel industry. Zervas, et al. (2017) found causal evidence of declining hotel profit due to the introduction of Airbnb in cities in Texas, USA. Similar research has been done in different markets. For example, with a more generalizable dataset in the United States (Dogru, et al., 2019) and outside the United States (Dogru, Hanks, Ozdemir, et al., 2020). Other research confirmed this relationship (Xie & Kwok, 2017; Dogru, Hanks, Mody, et al., 2020; Heo, et al., 2019).

Moreover, this research is also complementary on other research going into the externalities of different sharing economy companies. Another well-known example a company operating in the sharing economy is Uber, which offers a platform connecting passengers and privately operating drivers. Some research is done on the impact of Uber on the taxi market (Skok & Baker, 2018; Skok & Baker, 2019). Other research found that the presence of Uber and another ride-sharing platform, Lyft, impact the taxi industry in Austin, Texas (Hampshire, Simek, Fabusuyi, Di, & Chen, 2018).

3. Data

This chapter goes into the data collection procurement and the prepressing operations used to transform the data into variables. In this chapter, I describe the data I use in my analyses, and discuss key descriptives.

3.1 Data Collection

I use three data sources for my thesis: (1) a housing transaction dataset (obtained from Kadaster, an organization that monitors the Dutch real estate market), (2) an Airbnb listings dataset[4], and (3) an Amsterdam urban data (with the number of registered houses in the city of Amsterdam, obtained from CBS). I discuss each in turn.

House transaction data

The house transaction data contains data at the zip code level on all sold properties (incl. average transaction prices) in the city of Amsterdam between 2006 and 2021. The data is gathered and maintained by Kadaster, a Dutch organization that collects all records of all real estate transactions in the Netherlands[5]. The organization is part of the Dutch ministry of Interior and Kingdom Relations. The data I obtained from Kadaster contains the mean of all residential property sales in the municipality of Amsterdam. The data is aggregated per 4-digit zip code (N = 81 zip codes in Amsterdam) and per year (2006-2021; N = 15 years), for a total of 1,215 zip-code-year observations (N = 81 · 15 = 1,215)[6].

For the zip code, I relied on the first four numbers of a Dutch zip code rather than the entire zip code - which consists of four numbers followed by two characters (e.g., 1234 AB) -

[4] http://insideairbnb.com/
[5] https://www.kadaster.nl/
[6] The academic discount only applies for purchases lower than 1,500 observations

for two reasons. First, the entire Dutch zip code can be limited to only one street (since every house number needs to be unique for the entire zip code). This would lead to too sparse data, because of the small number of house transactions per year and unobservable effects in the heterogeneity of different houses in the entire zip code. If more expensive houses would be sold in a certain year, the average house transaction price would be distorted. When only selection the 4 number zip codes, the total number of zip codes in the municipality of Amsterdam is equal to 81. Second, in the context of this thesis a student discount only permitted to select a maximum of 1,500 observations. The Kadaster data contains the following variables: *zip_code*, *year*, and *transaction_price*.

Airbnb data

The Airbnb data is collected by a third party named InsideAirbnb, which collects Airbnb listings data and review data from different cities by using web scraping. The websites provide detailed information about the reviews and listings on the website. The listings data contains data of all listings within a certain city of country. In the Netherlands, only the information from Amsterdam is collected and stored. A possible alternative was to collect the data by using a web scraper, however by using this method historical listings could not be analyzed. The variables that were used for this research are: *latitude, longitude, number of reviews, first_review*, *last_review*, *host_id and host_since.* The total dataset contained 18,291 different Airbnb listings.

Amsterdam urban data

The data contains the number of registered houses within a certain zip code. This information is only used to calculate the Airbnb penetration rate of a zip code. The data is provided by the CBS, the Dutch Central Bureau of Statistics. The number of residential properties is collected for the period 2006 – 2020.

Government regulation

By doing desk research, I found that the municipality of Amsterdam decided to limit the maximum number of nights in which an individual can rent out her home (or a part of her home) via Airbnb (or via other websites such as Booking.com / Homeaway.com) to 30 nights per year[7]. This resolution started by the first of January 2019 and has no end date. Also, during this research I also analyzed if the municipality of Amsterdam or other governmental institution in the Netherlands (national and provinces) made other decisions regarding government intervention, however this relationship is not found. The municipality of Amsterdam only decided to block the presence of Airbnb listings in certain neighborhoods in Amsterdam near the city center, however this decision was reversed by a legal resolution[8].

3.2. Preprocessing

There were a couple of critical processes in that were taken in order to analyze the Airbnb penetration rate per year. The different preprocessing operations are linking a listing to a zip code, calculating when the listing was active and calculating the penetration rate.

Linking listing and zip code

The Airbnb database gives the listing's location by the variables: *latitude, longitude.* Both variables are given by six decimals. Therefore, the location can be analyzed with a 1.11-meter presession. The data transformation from location to zip code is done by using the Google

[7] https://www.amsterdam.nl/wonen-leefomgeving/wonen/woonruimte-verhuren/
[8] https://nos.nl/artikel/2372379-rechter-haalt-streep-door-airbnb-verbod-amsterdamse-centrumbuurten

Maps Geocoding API[9]. The API returned a six-character zip code, for that reason the last two letters were removed. A robustness check was performed by randomly selecting twenty different observations from the data. These observations were manually analyzed using Bing Maps. All twenty observations give the same zip code using the Google Maps Geocoding API and Bing Maps.

After analyzing the zip code per listing, thirteen observations were deleted from the dataset. These listings were not located in a zip code in the municipality of Amsterdam. Most of the thirteen outliers were located near the municipality border (e.g., Badhoevedorp and Amstelveen). Some observations were outliers and were located far outside the municipality, for example in Zwolle. The remaining dataset contains 18,262 listings.

Airbnb listings activity

A crucial element is defining in which an Airbnb listing is active. The activity depends on two concepts: entry and exit. This is the time in which the listing was actively listed on the home-sharing website. However, determining the Airbnb's activity is quite difficult to execute, since both the entry and exit date of the listing is unknown. The Airbnb dataset only displays the date in which a host (listings owner) joined Airbnb, but not the date in which the listing was put online. Moreover, the exit of the market is less clearly to determine. The Airbnb listing data does not define a moment of exit in the market. Previous research on home-sharing externalities proposes three methods in calculating the period of activity (Zervas, et al., 2017; Barron, et al., 2021).

The first method is to use the Airbnb *host_since* variable as the time of entry of all listings of the host. According to this method, the listing will be active until the end, meaning that the listing has no exit date. This method is quite unfitting to use, since it makes three big

[9] https://developers.google.com/maps/documentation/geocoding/overview

assumptions. Firstly, this method assumes that the listing will never leave the home-sharing platform, which of course is naturally not the case. Secondly, the method does not take into account that a single host can have multiple listings (Barron, et al., 2021). A thorough investigation of the data shows that only a small percentage of people (8.27%) has more than one listing and 2.10% has more two listings. A frequency table and histogram of the number of listings per host is given Appendix A. Thirdly, the model assumes that a listing between the entry and exit date is always active (Barron, et al., 2021), of course due to the sharing consumption idea of Airbnb the host will also use the listing personally.

A more sophisticated method is to use customer reviews time periods in which a listing was active. Zervas, et al. (2017) and Barron, et al. (2021) use these all-review data to calculate the TTL (time to live). The TTL is the time before and after a review was written in which an Airbnb listing is still active. In both papers, the start of the Airbnb's activity is when the host joins Airbnb, after that a host is active m months before a review was written and m months after that same review was written. Both papers used $m = 3$ and $m = 6$ to calculate het TTL for their second and third method.

These three methods were all used as different models in both research. In this research, I will also use three different methods to calculate the Airbnb activity. The first model uses the same method as the first model of Zervas, et al. (2017) and Barron, et al. (2021). The second model and third model will use an adjusted version of the TTL method to calculate the time in which a listing is active. The entry and exit date of each listing is calculated by the following formula:

$$\begin{gathered} Entry_i = first\_review - m \\ Exit_i = last\_review + m \end{gathered} \tag{1}$$

The formula proposes that the entry of the listing is *m* months before the first review is written and the exit is *m* months after the last review is written. Following the methodology of the two articles, the $m = 3$ for the second model and $m = 6$ for the third model. The adjusted method will result that the third assumption of the first model (no inactivity between the first and last review) still holds.

I have decided to only use the first and last review in this research compared to the second and third approach in Zervas, et al. (2017) and Barron, et al. (2021). The studies do not take seasonal factors into account, in particular the trend of renting out the listing in the summer (tourist season) and personally using the listing during het rest of the year. Also, the approach in Zervas, et al. (2017) and Barron, et al. (2021) does depends on the fact that every Airbnb listing receives equal amounts of reviews relative to the number of bookings. Comparably, differences in review dynamics should be equally divided per zip code. The Airbnb activity of an individual listing is used to the calculate the activity ratio per year. By only looking at the first and last review I want to minimize these effects. A value of 0 indicates that the Airbnb listings is not active throughout the whole year and 1 indicates that the Airbnb was active throughout the whole year.

Next, I aggregate the data of all listings into zip code level, by computing the number of active listings per zip code. Data cleaning is performed to delete observations which are not designed as residential areas. I deleted 7 zip codes in total which had less than 100 registered residential houses in 2019. These zip codes are: 1037, 1041, 1042, 1045, 1046, 1047 and 1101. After precise evaluation of the zip codes, the zip codes are located in the harbor and industrial area (Westpoort district) or in industrial areas in other parts of the city. Therefore, these observations were deleted from the dataset. The resulting dataset contains 75 different observations.

Barron et al. (2021) used the first method in their whole analysis. Zervas et al. (2017) compared the different methods in their main difference-in-difference analysis but used the first model in their additional analyses. The most important reason for their decisions is the seasonality affects in the Airbnb supply, since the TTL will be affected by peaks of consumer reviews during the summer. However, since the Airbnb activity data will be aggregated to a year and since only the first and last review are used to calculate Airbnb activity, this effect does not occur in this research. In this research, I use the third method considering the time that an Airbnb listing would be active on Airbnb but does not have any consumer reviews or does not get any guest. During this time an Airbnb would still be "active" even if they do not receive a consumer review.

Airbnb Penetration

The Airbnb penetration is calculated by dividing the Airbnb activity by the number of registered residential houses per year per zip code. The created variable indicates the ratio of active Airbnb listings compared to the number of houses. The Airbnb penetration rate is performed instead of using the number of active Airbnb listings because this variable takes the number of houses in the whole zip code into account. This method is not performed in earlier research (Barron, et al., 2021; Garcia-López, et al., 2020), however crucial for this dataset. As seen in Figure 1, the distribution of the number of houses among the different zip codes is quite large. Therefore, by using Airbnb penetration as variable could prevent validity bias with some zip codes that have a high number of Airbnb properties caused by a higher number of properties. This could especially be problematic for the city center since the neighborhoods have less residential properties than zip codes surrounding the city center. Using Airbnb penetration instead of the number of active Airbnb listings prevents biases of differences in number of residential properties. Consequently, a possible treat of using Airbnb penetration as independent variable is a misleading penetration because of a low number of residential houses.

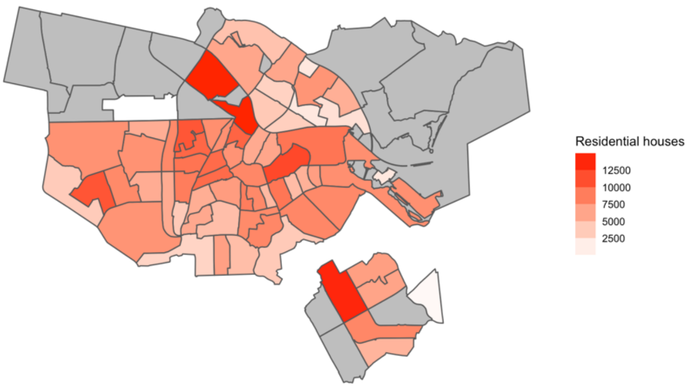

Figure 1: Distribution of residential houses in Amsterdam

Figure 2 shows the correlation between the Airbnb penetration and the Airbnb activity (method 3) in 2019. The plot shows that there are some outliers of observations that have low values for Airbnb activity, but high values for penetration. After analysis, the three outliers were zip codes outside the city of Amsterdam, but part of the municipality of Amsterdam. The zip codes 1026, 1027 and 1028 were deleted from the dataset, resulting in a dataset of 71 zip codes.

Urban data transformation

The urban data represented given by the Dutch Central Bureau of Statistics (CBS) does not have zip code as unit of analysis, but certain CBS districts, which naturally correspond to neighborhoods in Amsterdam. CBS used to use large neighborhoods (Dutch: wijk) as their unit of analysis, but now uses small neighborhoods (Dutch: buurt). The municipality of Amsterdam does contain 99 different large neighborhoods and 479 small neighborhoods. A contributing problem of this data collection is that some neighborhoods have overlapping zip codes, which was manually checked. For example, the large districts Jordaan and Grachtengordel-West do overlap in the 1015 and 1016 zip codes.

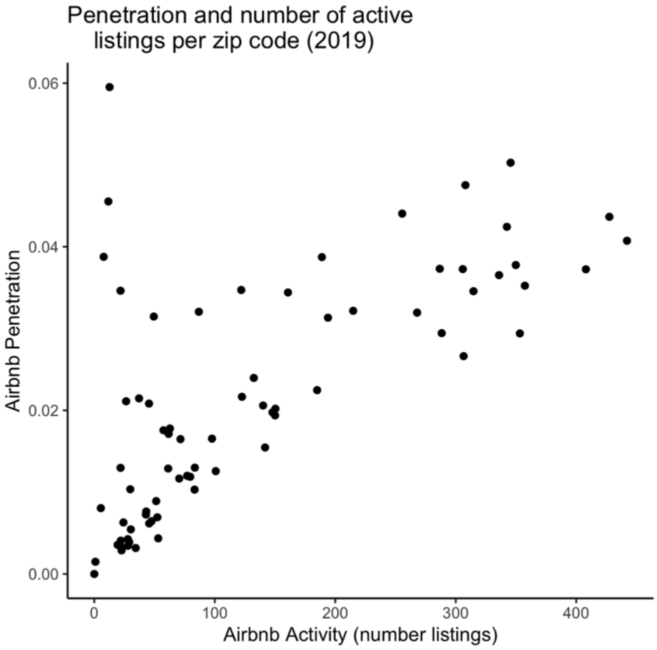

Figure 2: Graph of Airbnb penetration in 2019 and Airbnb activity in 2019

In this research, I used the 6-digit zip code to link the city district (both small and big) to the zip codes. Let zip code i be equal to a combination of city large districts d with weight w_{di}. In which w_{di} is the percentage of districts d that belongs to zip code i. For example, $w_{Jordaan,1015}$ is equal to 0.607 which means that 60.7% of Jordaan belongs to the 1015 zip code. The 6-digit zip code j is linked to a unique small neighborhood and a unique large neighborhood, with no 6-digit zip code that belongs to more than one neighborhood. The weight can be calculated by the sum of individual weightes of w_{dj}:

$$w_{di} = \sum_{i=0}^{n} w_{dj} \tag{2}$$

The individual weights are calculated by looking at the percentage of resident in districts d than live in 6-digit zip code j:

$$w_{di} = \frac{population_{dj}}{population_{d}} \tag{3}$$

The weights per city for districts d per zip code is given in Appendix C. For reliability reasons, the districts were matched by CBS district code since the spelling of the districts differ among different datasets. For most variables the value per zip code can be calculated by adding up the values of the different districts d and taken the weight w_{di}, where v_j is integer value, for example the number of residential properties. For values expressed in a mean, the calculation is done by taking the weighted average of the values of the districts, controlled by the weights of the districts.

Government regulation

It is expected that government regulation influences the relationship between the Airbnb penetration and the house transaction prices. Since 2019, the city of Amsterdam requires Airbnb listings owners to limit the number of Airbnb overnight stays per Airbnb listing to 60 nights per year. A dummy variable is recreated which has the value 0 when $t < 2018$ and 1 when $t \geq 2019$.

3.3. Summary Statistics

This paragraph gives a quick overview of the development of Airbnb in Amsterdam and the development of housing prices in Amsterdam.

Airbnb dynamics

The first Airbnb in Amsterdam was listed on Airbnb.com in 2008. As seen in Figure 3, the number of Airbnb listings in Amsterdam grew in 2012. However, the number of Airbnb's became significantly high from 2014 to 2018. From 2017 to 2019 the skewness of the growth decreased compared to the previous periods. From 2019 to 2020 there was a decrease in the number of active Airbnb listings when looking at the second and third method.

Method 1 **Method 2** **Method 3**

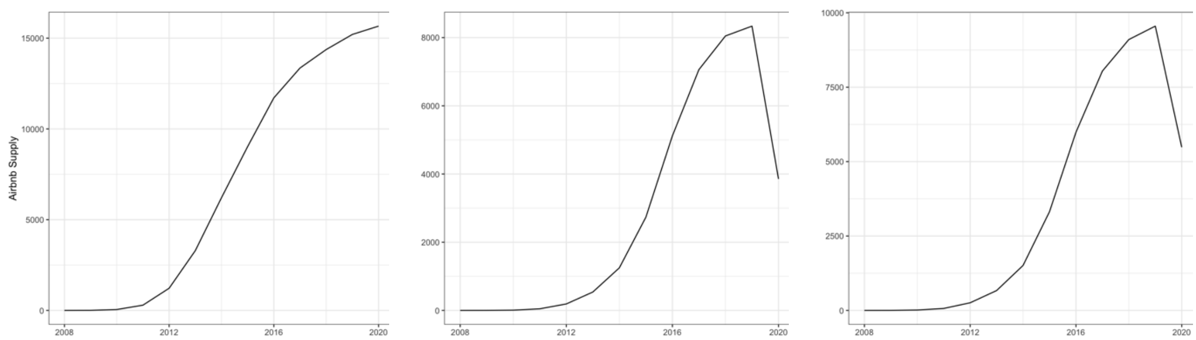

Figure 3: Total number of Airbnb listings per year calculated by the three methods

Figure 3 gives an overview of the number of Airbnb listings located in Amsterdam in 2014 and 2019. The activity of Airbnb listings is predominantly in the city center and the surrounding neighborhoods, in particular Amsterdam West that even has more absolute number of Airbnb's than in the city center. The number of Airbnb listings is lower in other residential parts of the city but still substantial, such as Amsterdam South, Amsterdam East and Amsterdam North. However, there is still a lot of activity in the north of Amsterdam South. Properly because of the presence of the museum districts of Amsterdam, which is located near the border of Amsterdam South and City Center. In comparison to the other parts of the city, there is little to no Airbnb activity in Amsterdam New-West and Amsterdam Southeast. Moreover, the graph also shows that the distribution of Airbnb listings around the city was kind of similar in 2014 and 2019.

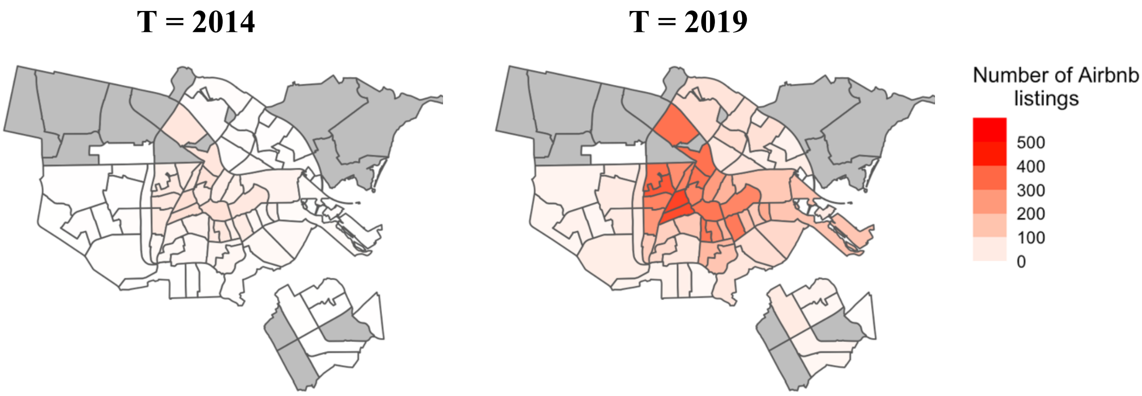

Figure 4: Number of Airbnb listings per zip code in Amsterdam[10]

House prices

The average house price development (averaged by zip codes) in the city of Amsterdam is displayed in Figure 5. As seen the house price is relatively stable between 2006 and 2011. The average house price in Amsterdam does even decrease slightly between 2011 and 2014. Between 2014 and 2020, the house prices in Amsterdam almost double from 300,000 in 2014 to 550,000 in 2020.

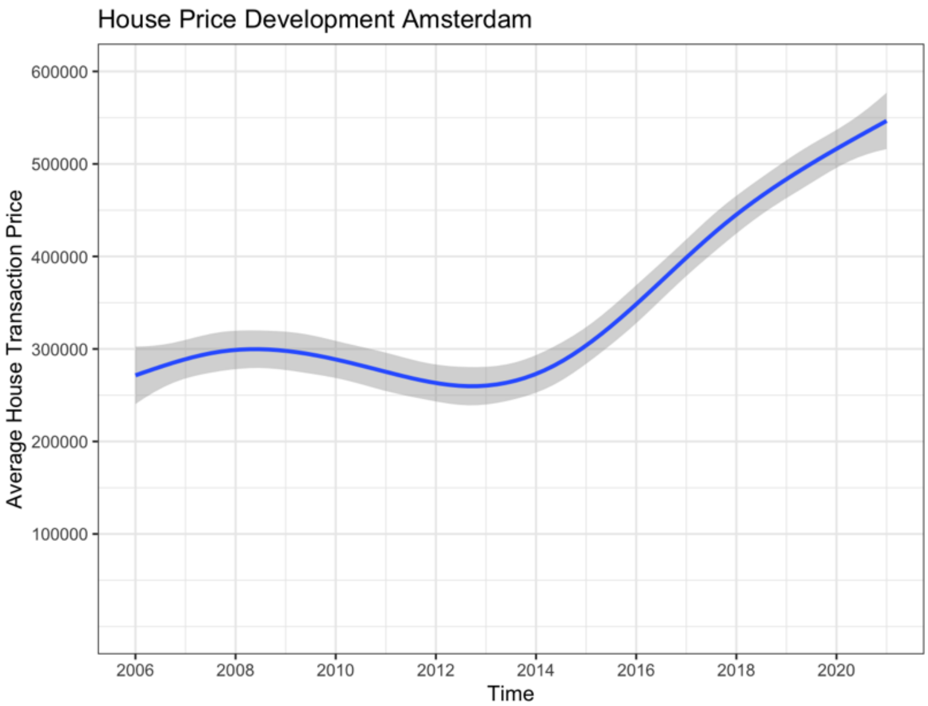

Figure 5: Average house price (averaged per zip code)

[10] The graphs are created by using R package *sf* in combination with the packages *raster* and *maptools*, the shapefile is provided by CBS (Centraal Bureau voor de Statistiek)

Before the impact of Airbnb, the house prices were quite stable in the city. The most expensive zip codes are located in the city center and especially in Amsterdam South.

T = 2006 **T = 2011**

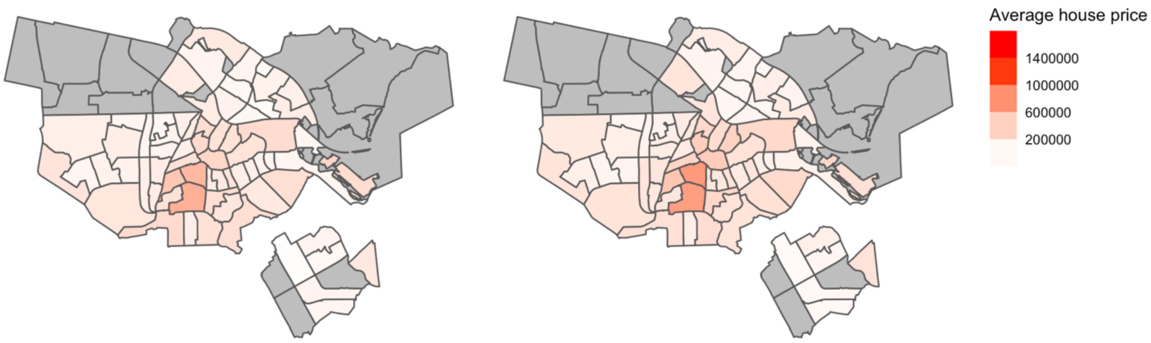

Figure 6: House price per zip code before Airbnb introduction

After the introduction of Airbnb, the house prices in Amsterdam rose quite intensely throughout the whole city, but especially in Amsterdam city center and Amsterdam North.

T = 2014 **T = 2019**

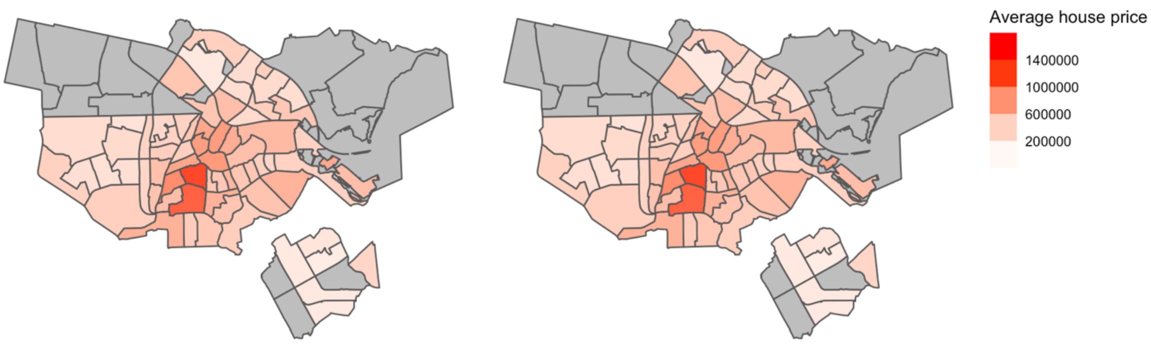

Figure 7: House price per zip code after Airbnb introduction

A considerable threat for validity is that the number of house transactions is so low that the house price is biased to positive or negative outliers. However, the Kadaster data contained the number of transactions, which allowed me to check if this is or isn't a serious threat. Close inspection of this value showed that there were three zip codes in which the average house transactions for $[2006 \leq t \leq 2020]$ was really low. These zip codes are 1044, 1105 and 1108, which are low populated areas near industrial and recreational areas. The average transaction quantity for these zip codes were 1.00, 1.00 and 1.33 respectively. In order to keep validity in this research, these zip codes were removed from the dataset. During the preprocessing operations (chapter 3.5) and the analysis of the dependent variable, certain zip codes were removed for specific reasons. A small summary of every data collection of zip code is given in Table 2. The resulting data sample consists of 68 different zip codes i and 15 different years t [2006, 2020].

Zip codes	**Treat to**	**Kind of city areas**	**Reason**
1037 1041 1042 1045 1046 1047 1101	Validity of independent variable	Industrial areas in Westpoort, industrial area near Slotendijk and business area Amsterdam Southeast	The zip codes had low values for Airbnb penetration because the number of residential properties in 2019 was lower than 100.
1026 1027 1028	Validity of independent variable	Towns outside the city of Amsterdam but within the municipality of Amsterdam.	These zip codes showed outlier values when comparing the Airbnb penetration to the number of Airbnb's due to a low number of residential houses.
1044 1105 1108	Validity of dependent variable	Industrial area in Westpoort, recreational area and business area Amsterdam Southeast	These zip codes had an extreme low number of transaction quantity when calculating the average house transaction price.
1014 1036	Missing values dependent variable	Industrial and residential	These zip codes did not have 16 years with transaction data, most likely because there were no transactions in the years with missing values

Table 2: Motivation of data cleaning process

4. Methodology

The dependent variable in this research is Υ_{it}, which is the average transaction price in the *housing market* for zip code i in year t, in which the year is between 2006 and 2020. Let Airbnb_pen_{it} be the average Airbnb penetration rate of zip code i in year t. Let $Gov\_intervention_t$ be a dummy variable that indicates whether *t* occurs before or after the government intervention in the home-sharing market in Amsterdam (i.e., it equals 0 before 2019 and 1 as of 2019). To test whether Airbnb_pen_{it} influences Υ_{it}, I run the following regression, which follows prior literature estimating "intervention effects", i.e., treatment effects of an exogenous intervention (see e.g., Viswanathan, Li, John, & Narasimhan, 2018):

$$\Upsilon_{it} = \alpha + \beta_1 \text{Airbnb\_Pen}_{it} + \beta_2 Gov_{intervention_t} + \mathbf{X}_{it} + \boldsymbol{\delta}_t + \epsilon_{it} \tag{1}$$

Equation (1) clarifies that I estimate the treatment effect of the governmental intervention limiting Airbnb's intensity through a pre- vs. post- analysis that controls for three sets of variables. First, I control for time- and zip-code-varying variables that may influence housing prices, and which I collect in the vector $\mathbf{X}_{it}$. Examples of such variables are population density and unemployment rate. Second, I control for time-varying factors that are zip-code independent and that may also influence housing prices. I collect such time-varying factors in the vector $\boldsymbol{\delta}_t$. Specifically, this vector contains year-specific variables aimed to capture market changes that occur over time and tend to affect all zip codes (e.g., fluctuations in macroeconomic variables). ϵ_{it} captures unobservable effects that may also influence Υ_{it}.

$$\begin{aligned}\Upsilon_{it} = {} & \alpha + \beta_1 \text{Airbnb\_Pen}_{it} + \beta_2 Gov\_internevtion_t \\ & + \beta_3 \text{Airbnb\_Pen}_{it} \cdot Gov\_internevtion_t + \mathbf{X}_{it} + \boldsymbol{\delta}_t + \epsilon_{it}\end{aligned} \tag{2}$$

Equation (2) clarifies if the effect of government intervention dependent on the zip code, or more precisely on the extent of Airbnb penetration in a given zip code. In other words, the interaction effect captured by β_3 measures whether housing prices in zip codes with more Airbnb listings were more or less affected by the governmental intervention than housing prices in zip codes with few Airbnb listings.

Time varying control variables ($\boldsymbol{\delta_t}$*)*

The time varying control variables ($\boldsymbol{\delta_t}$) are influenced over time t, however these variables are constant per zip code i. This research controls for three-time varying control variables: (1) gross national product, (2) consumer trust, and (3) tourist demand.

First, unlike previous research, this research does take market affects into account, since house transactional prices are dependent on the demand and supply. Therefore, the housing prices can be dependent on the national economy and the consumer willingness to buy expensive products. In this research, we incorporate the GNP (gross national product) of the Netherland per year.

Second, I account for the average consumer trust per year to further control for consumer hesitant to buy real estate due to financial distrust.

Third, similarly to Barron, et al. (2021) we control for tourist demand in this model. Barron, et al. (2021) scraped a large amount of tourist reviews of restaurants, hotels, and suchlike to determine tourist demand over time. In this study, Google trends are used to determine this variable. Using Google Trends has been helpful for making predictions (Choi & Varian, 2012). This method has been accurate in predicting customer demand for both country and city tourism rate (Önder, 2017). Google Trends gives the index value of search queries on Google, the index values are relative the highest value of the month with the most searches. In the month with the most amount of search queries the Google Trends value is equal to 100. For example, when the index value of Google Trends is equal to 50, it means that the amount of that particular search query was 50% when compared to the highest month. The average value for tourist demand is calculated by taking the mean of the trendline of searches of "Amsterdam". Moreover, the Google trends settings were put at the travel category for all web searches worldwide. The result of the Google search is visible in Figure 8.

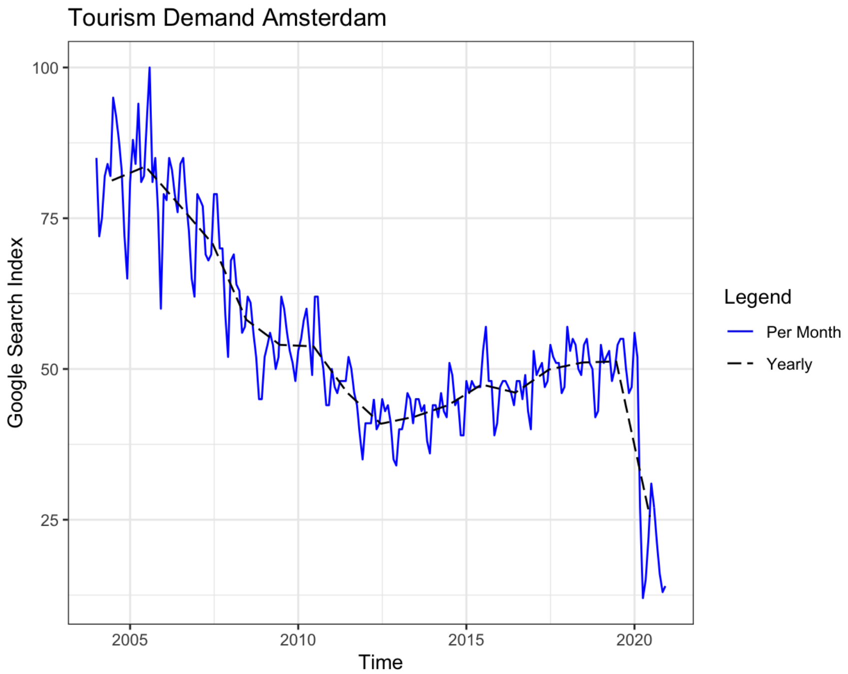

Figure 8: Google Search Trends of worldwide searches of "Amsterdam" in the travel category

Time and zip code varying control variables ($\mathbf{X}_{it}$)

Following the research of Barron, et al. (2021) the average number of restaurant locations is used to control for the rate of tourism in all zip codes. Unlike, Barron, et al. (2021), I will not use the number of restaurants in zip code i, but the number of restaurants in a 1 km distance for all residents in the area. Because of unavailability of complete data, the data is based on 2017. However, changes between 2006 and 2016 are not expected. The second variable calculation the rate of tourism is the number of hotels in a zip code, as suggested in

Barron, et al. (2021). Other research investigating the impact of Airbnb on rent prices and house transaction prices, also used the median household income, log population, college share, unemployment rate, population density, average age, rate of foreign residents and crime rate (Horn & Merante, 2017; Garcia-López, et al., 2020; Chang, 2020; Barron, et al., 2021). This research will investigate the average income, log population, unemployment rate, population density, average age, and rate of non-Western residents. The crime rate per post codes is only available for the period between 2010 and 2015. Due to the extent of this research, the period before 2010 will is assumed to be constant to 2010 and the period after 2015 is assumed to be constant to 2015. The college share is not incorporated in this study since of its unavailability and because the influence of college students on the house transaction / rental prices are expected to be minimal in the Netherlands, since the Netherlands / Amsterdam does not have college towns with high population of students. The crime rate is not incorporated due to the lack of available data.

5. Results

To gain a comprehensive understanding of the linear regression model, it is critical to understand the different variables of the model. Table 3 gives a basic statistical description of the different variables in the model.

Variables	$\bar{x}$	s	Min	Max	N
House_price	324,852.60	163,692.50	49,748.00	1,231,352.00	971
Airbnb_number	45.08	83.18	0	442.13	971
Airbnb_penetration	0.0065	0.0103	0	0.045	971
Goverment_intervention	0.13	0.34	0	1	971

Table 3: Descriptive analysis of variables in fixed-model regression

5.1. Analysis with average government intervention calculation

Table 4 provides the results of the linear regression. In all models the third method (based on consumer reviews | $m = 3$) is chosen. The different control variables used in this study are split in three groups. Firstly, the group *zip code controls* are the different controls that varies per zip code, which control for changes regarding inhabitants' characteristics (e.g. income) and neighborhood characteristics (e.g. density) per zip code over time. The *economic controls* are the economic changes over time and the *tourism controls* includes the controls for demand of tourism in the city of Amsterdam over time. Model 1 includes the correlation between the Airbnb penetration and Airbnb number of houses. The other models present the same relationship but then the correlation is controlled by the different control variables. The final model for equation (1) is model 4 since it has the highest R^2 and Adjusted R^2. Also, the model is controlled for all three controls.

	Dependent variable:			
	House Price (Model I)	House Price (Model II)	House Price (Model III)	House Price (Model IV)
Airbnb_penetration	6536226***	3031703***	1982721***	-320609
	(457216)	(347183)	(342192)	(401790)
Goverment_intervention	118366***	91535***	116444***	77468***
	(13960)	(8212)	(8097)	(11010)
Zip code control		✓	✓	✓
Tourism control			✓	✓
Economic control				✓
Constant	267026***	571722***	274084***	114581**
	(5222)	(55181)	(58995)	(91793)
Observations	971	971	971	971
R2	0.2538	0.7788	0.8027	0.8212
Adjusted R2	0.2531	0.7772	0.8011	0.8193
Residual Std. Error	141500 (df = 968)	77260 (df = 963)	73010 (df = 962)	69580 (df = 960)
F Statistic	329.7*** (df = 2; 968)	484.5*** (df = 7; 963)	489.3*** (df = 8; 962)	440.9*** (df = 10; 960)
Note:	*p<0.05; **p<0.01; ***p<0.001			

Table 4: Regression results

There is no significant correlation found between Airbnb penetration in a zip code and the average housing price in that zip code. Without the economic control the correlation is significant and has a large effect size and expected direction. However, after controlling for GDP and consumer trust, the relationship becomes insignificant, suggesting that GDP fluctuations are correlated both with housing prices and Airbnb penetration, which means that leaving out the GDP control creates a problem of endogeneity and biases this parameter estimate.

The expected relationship between government intervention of Airbnb and house price is significant when controlling for zip code, economic and tourism demand. However, the relationship is positive while there was a negative relation expected between the government intervention and the house price development. An important consideration is that there is no unseen relationship between the Airbnb penetration and the number of houses in a neighborhood. It is likely that the correlation between the variables is interfered by zip codes with a low number of houses, which causes high values for Airbnb penetration while the treatment effect is low. An extra regression analysis is performed to investigate this assumption, the results are shown in Table 5.

	Dependent variable:			
	House Price (Model V)	House Price (Model VI)	House Price (Model VII)	House Price (Model VIII)
Airbnb_number	691***	242**	127**	-96*
	(57)	(42)	(41)	(43)
Goverment_intervention	135684***	98437***	123731***	76693***
	(14118)	(8330)	(8095)	(10951)
Zip code control		✓	✓	✓
Tourism control			✓	✓
Economic control				✓
Constant	275817***	571722***	244938***	67287
	(5213)	(58167)	(61608)	(92330)
Observations	971	971	971	971
R2	0.2681	0.7692	0.7979	0.8212
Adjusted R2	0..2666	0.7675	0.7962	0.8193
Residual Std. Error	140200 (df = 968)	78920 (df = 963)	73010 (df = 962)	69580 (df = 960)
F Statistic	177.3*** (df = 2; 968)	458.5*** (df = 7; 963)	474.7*** (df = 8; 962)	440.9*** (df = 10; 960)
Note:	*p<0.05; **p<0.01; ***p<0.001			

Table 5: Regression results

The results of Table 5 are similar to the results of the first regression analysis of Table 4. However, when controlling for the first three controls the results seem to be significant, however the direction is negative instead of the expected positive effect. Another threat needing to investigate is the bias caused by the independent variable which does not capture the correct

Airbnb activity rate. Likely, this could influence the effect size and the significance of the relationship. As proposed in the methodology section, I will test the correlation in number of Airbnb listings and Airbnb penetration using the three different methods. The results are presented in Appendix D. All methods result in a negative relationship between Airbnb activity and the house price.

5.2. Analysis with interaction effect government intervention

Table 6 provides the result of equation (2) as proposed in the methodology. This time the government intervention variable is changed to a moderation variable.

	Dependent variable:			
	House Price (Model IX)	House Price (Model X)	House Price (Model XI)	House Price (Model XII)
Airbnb_penetration	6954027***	3715321***	2831657**	320175
	(511372)	(383186)	(366935)	(462322)
Goverment_intervention	144729***	130975***	171287***	106068***
	(20836)	(12660)	(12357)	(15060)
Goverment_intervention * Airbnb_penetration	-1995805***	-2683407***	-3614995***	-1791569**
	(1124892)	(659322)	(622841)	(646224)
Zip code control		✓	✓	✓
Tourism control			✓	✓
Economic control				✓
Constant	265161***	607663***	302069***	118123
	(5326)	(55448)	(58217)	(91483)
Observations	971	971	971	971
R2	0.3069	0.7826	0.8094	0.8226
Adjusted R2	0.3047	0.7808	0.8076	0.8206
Residual Std. Error	136200 (df = 968)	76640 (df = 962)	71800 (df = 961)	69340 (df = 959)
F Statistic	143.3*** (df = 3; 971)	432.8*** (df = 8; 962)	453.4*** (df = 9; 961)	404.3*** (df = 11; 959)
Note:	*p<0.05; **p<0.01; ***p<0.001			

Table 6: Regression results with interaction effect

As seen in Table 6, there is a significant interaction effect between housing price and government intervention of Airbnb, when government intervention is moderated by the Airbnb penetration rate. When government intervention is equal to 1 ($t \geq 2019$) the average house price increases with 106,068, however there is a negative moderating correlation with Airbnb penetration ($\beta_3 = -1.791{,}569, p = 0.01$). The lowest value for Airbnb penetration in the years with government regulation is 0.001748714, while the maximum value is 0.04535048. This means that the house prices in all neighborhoods still increased, but neighborhoods with higher Airbnb penetration increased in a much lower rate. An interaction plot of this relationship is shown in Figure 9. Also, in this analysis the relationship between Airbnb penetration and house prices is still positive when controlling for all other variables (model XII). This was not found during the previous regression analysis (model IV in Table 5 and model VIII in Table 6. Due to the highest R^2 and Adjusted R^2, model XIV is used as the final model in this research and is therefore used in the robustness checks and discussion chapter.

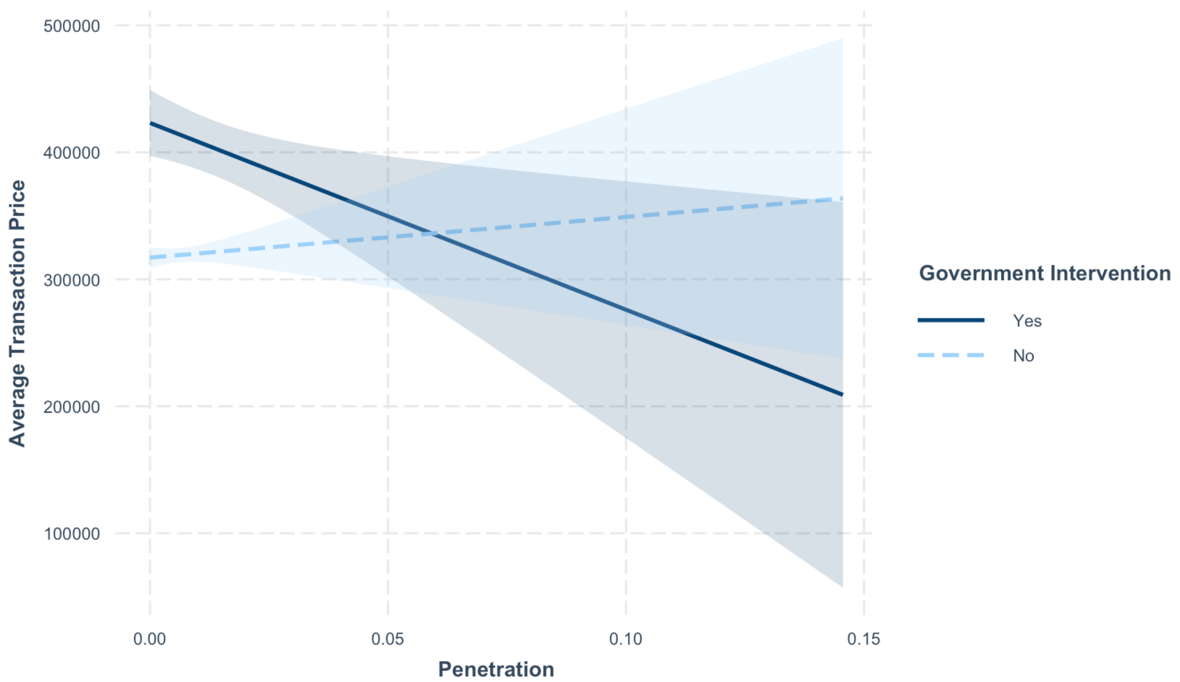

Figure 9: Plot of the interaction effect of government regulation and Airbnb penetration on average house prices

5.3. Robustness Check

There were three main treats that can influence the results of this analysis. Firstly, there might be an unseen relationship between previous house transaction prices of a zip code and the current transaction prices of a zip code. The '*lagged'* house price is calculated by taking the house transaction price one year ago (Υ_{it-1}). Both relationships regarding the effect of government intervention on house prices are significant in model XII are still significant in this model. The results are put in Appendix E.

Secondly, I tried to investigate if the relationships were robust to nonlinear changes in time. Therefore, the results were tested for both log time and squared time. When applying log time, both relationships regarding government intervention became highly insignificant ($p = 0.49$ and $p = 0.41$), indicating there they may be an unseen interference of time. When applying the squared time, the results remained robust. The results of the analysis are put in Appendix F.

Another threat to the results is the presence of multicollinearity due to the high number of variables in the model, which are caused by the controls. After looking into the variance inflation factor (VIF), I concluded that the chance of multicollinearity is quite low since none of the variables have values of VIF higher than 10.0.

6. Discussion

The goal of this research is to examine if we find empirical evidence for a positive correlation between house prices and Airbnb activity. There is no evidence found of such relation. Therefore, this research is not in line with earlier research on this topic that found significant relationships between house price development and Airbnb activity (Perez, et al., 2020; Chang, 2020; Barron, et al., 2021). However, in this research significant correlation between house prices and Airbnb activity is found without controlling for economic changes, which is also not performed in earlier research (Perez, et al., 2020; Chang, 2020; Barron, et al., 2021). The second objective of this research is to find evidence of house price changes due to government intervention of Airbnb. Evidence found that government intervention is correlated with house price development and that this relationship is moderated by the influence of Airbnb penetration.

The model found that government intervention led to an increase in housing prices, but this effect was larger for zip codes with low Airbnb penetration than for areas with high Airbnb penetration. A possible explanation for this relationship is that the government intervention in the house sharing market resulted in better urban livability due to the limited negative externalities caused by Airbnb in the housing market. Much more likely, however, the average increase in house price in the governmental intervention years is caused by sparsity in residential properties which is currently an issue for most neighborhoods in Amsterdam. Since the dataset does not contain any zip codes outside the jurisdiction of the municipality of Amsterdam all observations after 2018 were forced to follow the new home-sharing regulation. Therefore, the government regulation could be influenced by other unobserved variables that took place in 2019 and 2020.

6.1. Limitations

The main limitations in this research are data sparseness and some data quality issues. Firstly, the CBS-database did not contain information of urban and demographic information per zip code but only on neighborhood level. This solution is solved by taking the weighted average of (partial) neighborhoods in a certain zip code. This approach does contain a lot of biases. Firstly, this approach assumes that the urban and demographic statistics within a certain neighborhood is evenly distributed among the neighborhoods. Of course, this is not the case. Secondly, in this research changes in weights among neighborhoods and zip codes is not considered, the weights (such as described in Appendix D) is calculated by data in 2017. Therefore, changes in weights due to the building and removal of residential properties is not considered. Moreover, this research did use the mean of transaction prices per zip code in a specific year. Taking this variable into account can create bias in two specific ways. Firstly, it can cause validity problems due to extremely high or low house price transactions, therefore the variable could take proportionally high values. Secondly, if the number of transactions is considerably low the mean can be substantially different throughout the years due to the limited number of observations which was used to calculate the mean. The data is directly delivered and collected by Kadaster, therefore a reliability analysis could not be performed, since only the mean and the number of transactions is given by Kadaster. An alternative would be to use measurement that uses previous transaction data to stabilize the mean transaction value. In the Netherlands the *WOZ-waarde* could be used. Previous research also used this variable by using the Zillow Index (Barron, et al., 2021). Consequently, this variable could also be biased since rapid changes in house price development cannot be detected since they are averaged out by previous transactions. Lastly, due to the unavailability of observations which are not exposed to the government intervention, it is likely that the government intervention is highly correlated with unseen factors (e.g. house scarcity) in the years 2019 and 2020.

6.2. Areas for future research

Future research should focus on three important aspects. First, research should use house transaction prices and house price indexes (WOZ and Zillow Index) for the calculation of housing prices. Also, research should focus on determining the optimal method in which the supply of Airbnb listings is calculated. Previous research and this research have used three measurements to calculate housing price, but it remains unclear which method truly matches Airbnb supply. To determine this, research should focus on how long an Airbnb listing stays active after they got a review and how often a listing receives a review. Also, current research assumes that all Airbnb listings are similarly active, however there could be some changes in different neighborhoods and cities. For example, I assume that homeowners outside the city and in inner-city suburbs are more likely to rent out their home if they are not using it, while corporate investors that buy out properties to list them on Airbnb are more likely to do it near the city center since these neighborhoods are in higher demand (since they are closer to sightseeing). Also, future research should focus on investigating if government regulation has a negative effect on Airbnb supply and therefore house transaction prices. It is important that this should be done when there is a substantial number of years in which the government intervention is active and that the interaction should be compared to other cities where there is no government intervention, for example in a difference-in-difference experiment design.

7. Acknowledgements

I would like to express my sincere gratitude towards my coach, Dr Nuno M. Almeida Camacho, for providing feedback on this thesis and for their continuous support throughout the thesis trajectory. Also, I would like to thank my family and friends for their support throughout not only my thesis trajectory but also throughout the whole educational career.

Bibliography

Ayouba, K., Breuillé, M.-L., Grivault, C., & Le Gallo, J. (2020). Does Airbnb Disrupt the Private Rental Market? An Empirical Analysis for French Cities. *International Regional Science Review*, 43(1-2), 76-104. https://doi.org/10.1177/0160017618821428

Barron, K., Kung, E., & Proserpio, D. (2021). The Effect of Home-Sharing on House Prices and Rents: Evidence from Airbnb. *Marketing Science*, 40(1) 23-47. https://doi.org/10.1287/mksc.2020.1227

Belk, R. (2010). Sharing. *Journal of Consumer Research*, 36(5), 715–734. https://doi.org/10.1086/612649

Belk, R. (2014). You are what you can access: Sharing and collaborative consumption online. *Journal of Business Research*, 67(8), 1595-1600. https://doi.org/10.1016/j.jbusres.2013.10.001

Bloom, N., Garicano, L., Sadun, R., & Van Reenen, J. (2014). The Distinct Effects of Information Technology and Communication Technology on Firm Organization. *Management Science*, 60(12), 2859–2885. https://doi.org/10.1287/mnsc.2014.2013

Chang, H-H. (2020). Does the room sharing business model disrupt housing markets? Empirical evidence of Airbnb in Taiwan. *Journal of Housing Economics*, 49, 101706. https://doi.org/10.1016/j.jhe.2020.101706

Dongru, T., Hanks, L., Ozdemir, O., Kizildag, M., Ampountolas, A., & Demirer, I. (2020a). Does Airbnb have a homogenous impact? Examining Airbnb’s effect on hotels with different organizational structures. *International Journal of Hospitality Management*, 86, 102451. https://doi.org/10.1016/j.ijhm.2020.102451

Dogru, T., Hanks, L., Mody, M., Suess, C., & Sirakaya-Turk, E. (2020b). The effects of Airbnb on hotel performance: Evidence from cities beyond the United States. *Tourism Management*, 79, 104090. https://doi.org/10.1016/j.tourman.2020.104090

Dogru, T., Mody, M., Suess, C., McKGinley, S., & Line, N.D. (2020c). The Airbnb paradox: Positive employment effects in the hospitality industry. *Tourism Management*, 77, 104001. https://doi.org/10.1016/j.tourman.2019.104001

Dogru, T., Mody, M. & Suess, C. (2019). Adding evidence to the debate: Quantifying Airbnb's disruptive impact on ten key hotel markets. *Tourism Management*, 72, 27-38. https://doi.org/10.1016/j.tourman.2018.11.008

Eckhardt, G. M., Houston, M.B., Jiang, B., Lamberton, C., Rindfleisch, A., & Zervas, G. (2019). Marketing in the Sharing Economy. *Journal of Marketing*, 83(5), 5-27. https://doi.org/10.1177/0022242919861929

Edelman, B. G. & Luca, M. (2014). Digital Discrimination: The Case of Airbnb.com. HBS Working Paper 14-054, Harvard Business School, Boston.

Garcia-López, M.-À., Jofre-Monseny, J., Martínez-Mazza, R., & Segú, M. (2020). Do short-term rental platforms affect housing markets? Evidence from Airbnb in Barcelona. *Journal of Urban Economics*, 119, 103278. https://doi.org/10.1016/j.jue.2020.103278

Hampshire, R., Simek, C., Fabusuyi, T., Di, X., & Chen, X. (2018). Measuring the Impact of an Unanticipated Disruption of Uber/Lyft in Austin, TX. *Working Paper*, http://doi.org/10.2139/ssrn.2977969

Heo, C. Y., Blal, I., & Choib, M. (2019). What is happening in Paris? Airbnb, hotels, and the Parisian market: A case study. *Tourism Management*, 70, 78-88. https://doi.org/10.1016/j.tourman.2018.04.003

Hilton Worldwide, (2020). 2019 Annual Report. http://www.corporatereport.com/hilton/2019/ar/downloads/hilton_2019_ar.pdf.

Horn, K., & Merante, M. (2017). Is home sharing driving up rents? Evidence from Airbnb in Boston. *Journal of Housing Economics*, 38, 14-24. https://doi.org/10.1016/j.jhe.2017.08.002

InterContinental Hotels Group, (2021). 2020 Annual Report. https://www.ihgplc.com/en/investors/annual-report.

Köbis, N. C., Soraperra, I., & Shalvi, S. (2021). The Consequences of Participating in the Sharing Economy: A Transparency-Based Sharing Framework. *Journal of Management*, 47(1), 317–343. https://doi.org/10.1177/0149206320967740

Kumar, V., Lahiri, A. & Dogana, O. B. (2018). A strategic framework for a profitable business model in the sharing economy. *Industrial Marketing Management*, 69, 147 - 160. https://doi.org/10.1177/0149206320967740

Lee, D. (2016). How Airbnb Short-Term Rentals Exacerbate Los Angeles's Affordable Housing Crisis: Analysis and Policy Recommendations. *Harvard Law & Policy Review*, 229– 254.

Lusch, R. F., & Nambisan, S. (2015). Service innovation: A service-dominant logic perspective. *MIS Quarterly*, 39(1), 155-175. http://doi.org/10.25300/MISQ/2015/39.1.07

Marriott International, (2021). 2020 Annual Report. https://marriott.gcs-web.com/static-files/c5e1faef-f1e5-40e3-bd70-5efbbb929a7f.

Nieuwland, S., & van Melik, R. (2018). Regulating Airbnb: how cities deal with perceived negative externalities of short-term rentals. *Current Issues in Tourism*, 23(7), 811-825. https://doi.org/10.1080/13683500.2018.1504899

Skok, W., & Baker, S. (2018). Evaluating the impact of Uber on London's taxi service: A strategic review. *Knowledge and Process Management*, 25(4), 232-246. https://doi.org/10.1002/kpm.1575

Skok, W., & Baker, S. (2019). Evaluating the impact of Uber on London's taxi service: A critical review of the literature. *Knowledge and Process Management*, 26(1), 3-9. https://doi.org/10.1002/kpm.1573

Viswanathan, M., Li, X., John, G., & Narasimhan, O. (2018). Is cash king for sales compensation plans? Evidence from a large-scale field intervention. *Journal of Marketing Research,* 55(3), 368-381. https://doi.org/10.1509/jmr.14.0290

Xie, K. L., & Kwok, L. (2017). The effects of Airbnb's price positioning on hotel performance. International *Journal of Hospitality Management*, 67, 174-184. https://doi.org/10.1016/j.ijhm.2017.08.011

Zervas, G., Proserpio, D. & Byers, J. W., 2017. The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry. *Journal of Marketing Research*, 54(5), 687-705. https://doi.org/10.1509/jmr.15.0204

Appendix A

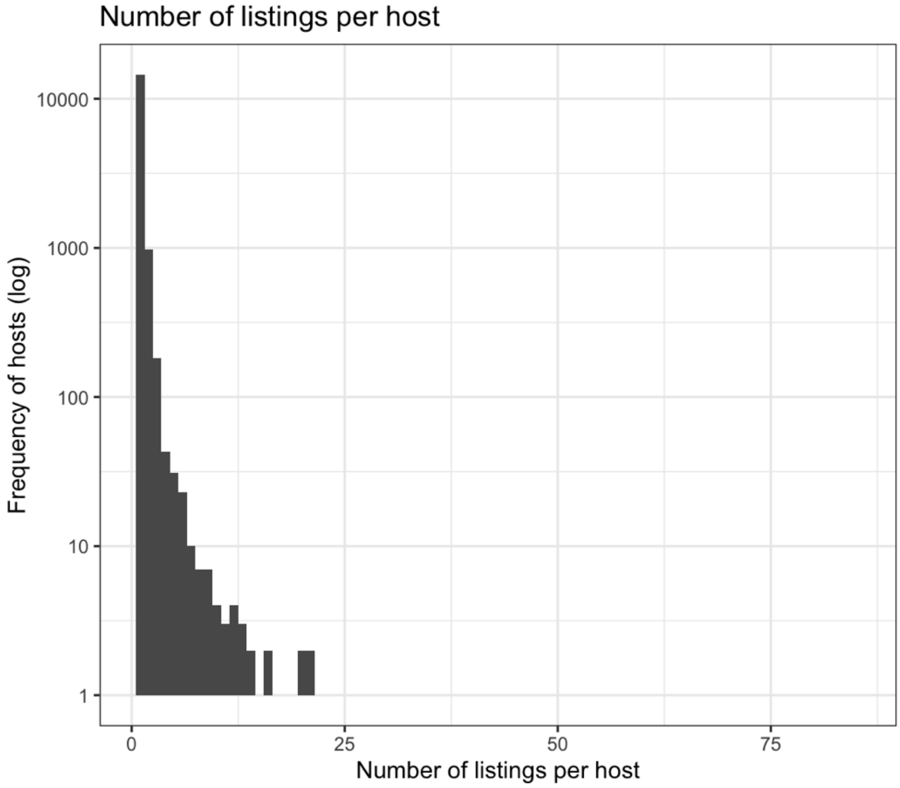

Figure 10: Histogram of the frequency of host with multiple listings

Number of listings per host	Number of observations (n)	Frequency
1 listing	14495	91.73%
2 listings	975	6.17%
3 listings	181	1.15%
4 listings	43	0.27%
5 listings	31	0.20%
>6 listings	77	0.49%

Total number of hosts is N = 15802

Table 7: Histogram of the frequency of host with multiple listings

Appendix B

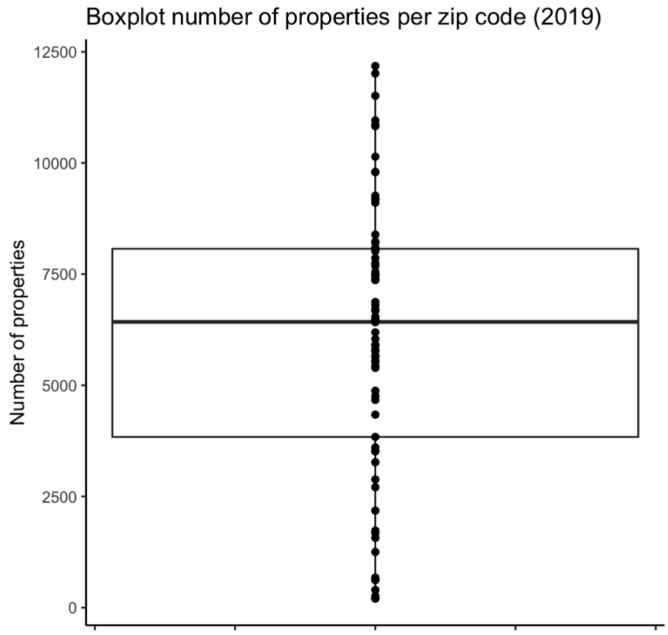

Figure 11: Boxplot of number of properties per zip code

Appendix C

Zip code	Neighborhood	Weight
1011	Nieuwmarkt/Lastage	1.000
	Oostelijke Eilanden/Kadijken	0.000
1012	Burgwallen-Nieuwe Zijde	0.999
	Burgwallen-Oude Zijde	1.000
1013	Haarlemmerbuurt	1.000
	Westelijk Havengebied	0.699
	Houthavens	0.947
	Spaarndammer- en Zeeheldenbuurt	0.997
1014	Spaarndammer- en Zeeheldenbuurt	0.003
	Sloterdijk	1.000
	Westelijk Havengebied	0.012
	Houthavens	0.053
1015	Grachtengordel-West	0.490
	Jordaan	0.607
	Frederik Hendrikbuurt	0.005
1016	Grachtengordel-West	0.510
	Jordaan	0.393
	Burgwallen-Nieuwe Zijde	0.001
1017	Grachtengordel-Zuid	1.000
	De Weteringschans	1.000
1018	Oostelijke Eilanden/Kadijken	0.996
	Weesperbuurt/Plantage	1.000
1019	Oostelijk Havengebied	1.000
	Oostelijke Eilanden/Kadijken	0.004
1021	IJplein/Vogelbuurt	0.819
	Noordelijke IJ-oevers Oost	0.493
1022	IJplein/Vogelbuurt	0.173
	Noordelijke IJ-oevers Oost	0.448
	Nieuwendammerdijk/Buiksloterdijk	0.008
	Buikslotermeer	0.000
	Elzenhagen	0.580
	Waterland	0.081
1023	Nieuwendammerdijk/Buiksloterdijk	0.292
	Tuindorp Nieuwendam	1.000
	Noordelijke IJ-oevers Oost	0.060
	Waterland	0.335
1024	Waterlandpleinbuurt	1.000
1025	Buikslotermeer	1.000
	Nieuwendammerdijk/Buiksloterdijk	0.619
	IJplein/Vogelbuurt	0.008
	Tuindorp Buiksloot	1.000
	Elzenhagen	0.420
1031	Volewijck	0.498
	Noordelijke IJ-oevers West	0.424
1032	Volewijck	0.502

	Noordelijke IJ-oevers West	0.246
1033	Oostzanerwerf	0.172
	Tuindorp Oostzaan	0.831
	Noordelijke IJ-oevers West	0.311
1034	Banne Buiksloot	1.000
	Kadoelen	0.013
	Noordelijke IJ-oevers West	0.018
	Nieuwendammerdijk/Buiksloterdijk	0.081
1035	Oostzanerwerf	0.817
	Kadoelen	0.987
	Noordelijke IJ-oevers West	0.000
1036	Tuindorp Oostzaan	0.169
1043	Bedrijventerrein Sloterdijk	0.357
	Westelijk Havengebied	0.036
1051	Staatsliedenbuurt	0.825
	Centrale Markt	1.000
	Landlust	0.000
1052	Staatsliedenbuurt	0.175
	Frederik Hendrikbuurt	0.995
	Da Costabuurt	0.225
	Kinkerbuurt	0.133
1053	Da Costabuurt	0.775
	Kinkerbuurt	0.867
	Van Lennepbuurt	1.000
1054	Helmersbuurt	1.000
	Vondelbuurt	1.000
	Overtoomse Sluis	0.991
1055	De Kolenkit	0.118
	Erasmuspark	0.694
	Landlust	0.833
1056	Van Galenbuurt	1.000
	De Kolenkit	0.093
	Erasmuspark	0.306
	Geuzenbuurt	1.000
	Landlust	0.167
1057	Hoofdweg e.o.	1.000
	Chass<e9>buurt	1.000
	Overtoomse Veld	0.092
1058	Westindische Buurt	1.000
	Overtoomse Veld	0.062
	Westlandgracht	0.151
	Hoofddorppleinbuurt	0.579
1059	Hoofddorppleinbuurt	0.421
	Westlandgracht	0.163
1060	Lutkemeer/Ookmeer	0.000
	Middelveldsche Akerpolder	0.694
1061	Overtoomse Veld	0.616
	De Kolenkit	0.789

1062	Overtoomse Veld	0.230
	Westlandgracht	0.686
	Slotervaart Noord	0.000
	Slotervaart Zuid	0.000
1063	Slotermeer-Noordoost	1.000
	Slotermeer-Zuidwest	0.198
1064	Slotermeer-Zuidwest	0.799
	Slotervaart Noord	0.308
1065	Slotervaart Noord	0.692
	Slotervaart Zuid	0.675
1066	Slotervaart Zuid	0.325
	Sloter-/Riekerpolder	1.000
	Erasmuspark	0.000
1067	Geuzenveld	1.000
	Lutkemeer/Ookmeer	0.878
	Eendracht	1.000
	Slotermeer-Zuidwest	0.003
1068	Osdorp-Oost	1.000
	Lutkemeer/Ookmeer	0.122
1069	Osdorp-Midden	1.000
	De Punt	1.000
	Middelveldsche Akerpolder	0.306
1071	Museumkwartier	1.000
	Overtoomse Sluis	0.000
	Vondelbuurt	0.000
1072	Oude Pijp	0.533
	Nieuwe Pijp	0.481
1073	Oude Pijp	0.292
	Nieuwe Pijp	0.310
	Zuid Pijp	0.630
1074	Oude Pijp	0.174
	Nieuwe Pijp	0.209
	Zuid Pijp	0.370
1075	Willemspark	1.000
	Schinkelbuurt	1.000
	Stadionbuurt	0.095
	Overtoomse Sluis	0.009
1076	Stadionbuurt	0.903
	Prinses Irenebuurt e.o.	0.159
	Zuidas	0.010
1077	Apollobuurt	1.000
	Stadionbuurt	0.002
	Stadionbuurt	0.002
	Zuidas	0.051
	Prinses Irenebuurt e.o.	0.841
1078	IJselbuurt	1.000
	Scheldebuurt	0.632
	Zuidas	0.017

1079	Scheldebuurt	0.368
	Rijnbuurt	1.000
1081	Buitenveldert-West	0.392
	Zuidas	0.072
1082	Buitenveldert-Oost	0.159
	Buitenveldert-West	0.608
	Zuidas	0.517
1083	Buitenveldert-Oost	0.841
	Zuidas	0.333
1086	IJburg West	0.284
	Zeeburgereiland/Nieuwe Diep	0.015
1087	IJburg West	0.716
	Zeeburgereiland/Nieuwe Diep	0.006
	IJburg Zuid	1.000
	IJburg Oost	0.000
	Hoofdweg e.o.	0.000
1091	Oosterparkbuurt	0.659
	Weesperzijde	1.000
	Transvaalbuurt	0.437
1092	Oosterparkbuurt	0.341
	Dapperbuurt	0.001
	Transvaalbuurt	0.563
1093	Dapperbuurt	0.999
1094	Indische Buurt West	1.000
1095	Indische Buurt Oost	1.000
	Zeeburgereiland/Nieuwe Diep	0.979
1096	Omval/Overamstel	0.984
1097	Frankendael	1.000
	Omval/Overamstel	0.016
	Betondorp	1.000
1098	Middenmeer	1.000
1102	Bijlmer Centrum (D,F,H)	1.000
1103	Bijlmer Oost (E,G,K)	0.512
1106	Holendrecht/Reigersbos	0.645
	Gein	0.543
	Bijlmer Centrum (D,F,H)	0.000
	Nellestein	0.003
1107	Gein	0.457
	Holendrecht/Reigersbos	0.355
1108	Nellestein	0.997
1109	Driemond	1.000

Weight is rounded to the third decimal

Table 8: Table of corresponding neighborhoods and zip codes with weight

Appendix D

	Dependent variable:					
	House Price	House Price	House Price	House Price	House Price	House Price
Airbnb_number (M1)	-44** (26)					
Airbnb_number (M2)		-34 (43)				
Airbnb_number (M3)			-96* (43)			
Airbnb_penenetration (M1)				-9904** (245280)		
Airbnb_penenetration (M2)					338165 (423018)	
Airbnb_penenetration (M3)						-320609 (401790)
Goverment_intervention	64020*** (13217)	-47272** (14454)	76693*** (10951)	63403*** (13237)	41156** (14727)	77468*** (11010)
Zip code control	✓	✓	✓	✓	✓	✓
Tourism control	✓	✓	✓	✓	✓	✓
Economic control	✓	✓	✓	✓	✓	✓
Constant	38245 (98156)	-499350*** (99450)	67287 (92330)	74660 (96252)	-470533*** (97901)	67287 (92330)
Observations	971	971	971	971	971	971
R^2	0.8279	0.8265	0.8212	0.8274	0.8394	0.8212
Adjusted R^2	0.8259	0.8246	0.8193	0.8253	0.8374	0.8193
Residual Std. Error	70300 (df = 960)	63710 (df = 963)	69580 (df = 960)	70420 (df = 960)	63710 (df = 960)	69580 (df = 960)
F Statistic	400.4*** (df = 10; 960)	435.2*** (df = 10; 960)	440.9*** (df = 10; 960)	398.7*** (df = 10; 960)	435.3*** (df = 10; 960)	440.9*** (df = 10; 960)
Note:	$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$					

Table 9: Regression Analysis with all methods for Airbnb supply calculation

Appendix E

	Dependent variable:
	House Price
Airbnb_penetration	442260
	(276894)
Goverment_intervention	21247*
	(9589)
Goverment_intervention * Airbnb_penetration	-965278*
	(384739)
Zip code control	✓
Tourism control	✓
Economic control	✓
Lagged price control	✓
Constant	-14118
	(54493)
Observations	908
$R2$	0.9412
Adjusted $R2$	0.9404
Residual Std. Error	1194 (df = 895)
F Statistic	143.3*** (df = 12; 895)
Note:	*p<0.05; **p<0.01; ***p<0.001

Table 10: Robustness check lagged price[11]

[11] Because lagged prices in 2006 the number of observations is lower.

Appendix F

	Dependent variable:	
	House Price	House Price
Airbnb_penetration	-352392	747951
	(430221)	(463958)
Goverment_intervention	-11282	169662***
	(16627)	(19375)
Goverment_intervention * Airbnb_penetration	515246	-2445343***
	(623186)	(650565)
Zip code control	✓	✓
Tourism control	✓	✓
Economic control	✓	✓
Log time control	✓	
Squared time control		✓
Constant	-117162	-171253
	(86453)	(106547)
Observations	971	971
R2	0.8488	0.8273
Adjusted R2	0.8469	0.8252
Residual Std. Error	64040 (df = 958)	68440 (df = 958)
F Statistic	448.2*** (df = 12; 958)	382.5*** (df = 12; 958)
Note:	*p<0.05; **p<0.01; ***p<0.001	

Table 11: Robustness check time