

Master Thesis

Airbnb listing prices in
Amsterdam and distance to
tourist spots

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Abstract

This study focuses on the association between Airbnb listing prices and the distance to tourist spots in the city center of Amsterdam. The results are based on hedonic pricing models, estimated by ordinary least squares and quantile regression. This research aims to build on existing literature by developing a method that identifies the determinants of Airbnb accommodation prices in Amsterdam. The most important findings are that tourist spots have an important factor for the price determination of Airbnb, especially in areas between 0,2 km and 1 km. Tourists are willing to pay more for an Airbnb that is closely located to a tourist spot. There are differences between the higher segment preferences and lower segment preferences. The lower segment of Airbnb renters is less sensitive to locations and are more able to walk compared to the higher segment of Airbnb renters. The results of this study are useful for policymakers in Amsterdam to understand the spatial pattern of Airbnb. By understanding the importance of amenities, Amsterdam can increase its livability and can create a sustainable future for the city.

Keywords: Airbnb, Tourist spots, location, hedonic model

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1. Introduction

The world around us is changing, and in this rapidly evolving world, the sharing economy is growing in influence. This is accompanied by new business (models) such as Airbnb. Since its establishment 12 years ago, it is now active in over 100,000 cities across 220 countries. With 7 million listings worldwide, it has rented to 500 million guests (Airbnb, 2020). Almost 80 percent of its bookings are made by foreigners (Airbnb, 2020), which illustrates the importance of Airbnb for cities that wish to stimulate from tourism. Therefore, Airbnb's rapid growth caught the attention of Dutch municipalities and policymakers (Dutchnews, 2020).

The rise of Airbnb seems to have a mixed impact on local economies. On the one hand, Ecorys (2018), found that 34 percent of tourism expenditures is spent on local accommodations. On the other hand, negative side-effects exist; for instance, 80 percent of the people who live in Amsterdam's city center experience increased nuisance (NRC, 2020). Furthermore, research shows that Airbnb listings puts more pressure on the housing market and inflates property prices (Sheppard, 2016 and Bijl, 2016).

Sainaghi and Baggio (2020), focused in their research on the relationship between hotels and Airbnb and found that Airbnb can be a substitute for traditional accommodations rather than attracting new tourism flows. Furthermore, they found that the biggest advantage of Airbnb is its location since most Airbnb listings are in proximity of the city center which is attractive for tourists. This gives them an edge over hotels since the location of hotels is usually regulated. However, the playing field seems to change in favor of hotels as cities such as Amsterdam have implemented restrictions for Airbnb listings. In the city core, Airbnb has been banned, and areas around the city's core have restrictions for 30 days' rental (Airbnb, 2020). Nevertheless, the bookings of Airbnb in Amsterdam are still high over the last years (Airbnb,2020).

Many studies have already investigated the price determinants for Airbnb listings prices in urban areas. For instance, Wang and Nicolau (2017) and Porges (2013), investigated basic price determination levels, such as reviews, rental prices, and type whole renting. The location also plays an important role in price determination. Perez-Sanchez et al.(2018), looked at the impact of beaches and Airbnb prices in Southern Europe. Although Amsterdam has no beaches, the research done by Perez-Sanchez et al.(2018), reveal another factor that impacts Airbnb, namely the amount of regulation as Southern European cities are less strictly regulated. This stands in contrast to Amsterdam, where the municipality, through urban planning, influences, and controls the areas where hotels and Airbnb can be located. In addition, urban planning influences the distribution of tourism over the city. Spreading tourism over the city can increase livability and decrease negative spillovers such as noise pollution (Guttentag, 2015). If the tourism flow is well managed, positive results related to urban sustainability can be obtained such as local and tourist interaction, lower vacancy rates and increased livability (Porges, 2013). In other words, to increase urban sustainability it is crucial to understand how tourism flows works and spreads across the city. According to Shoval and Raveh (2004), tourists are very selective in the way they use

the city as they tend to concentrate in specific areas of a city. This study showed the importance of tourist attractions in areas. A tourist wants to stay closer to multiple tourist spots. This pattern was already observed by an older study of Arbel and Pizam, (1977) who focused on hotel locations and tourist spots. This can also be the case for Airbnb. However, these studies are dated, and Airbnb was nonexistent.

For real estate investors, it is crucial to understand the significant role of locations in price determinations of Airbnbs. This role stems from the further professionalization of Airbnb listings properties (Getyourpad,2020). As a result of the growing popularity of Airbnb listings, more professional managers are entering the Airbnb market. These managers act as agents to handle Airbnb's facility activities, which involve cleaning, check-outs, damage, and other hosting-related issues on behalf of the principal. As a consequence, Airbnb increase commissions for the Airbnb listing incorporated in the rental price. Therefore, professional Airbnb managers need to deal with higher costs to remain competitive with other rentals. This pressures the Airbnb- and Amsterdam housing market. Investors are interested in the capitalization rate associated with rental income and the property's purchase price (Gallin, 2006). At the same time, professional Airbnb managers are interested in returns associated with locations. However, empirical analysis for professional Airbnb managers and price determination of location is lacking.

Consequently, it seems that there is ample evidence that locations are an essential part of the rental price of Airbnb. Most of the research is focused on the relationship between distance to city cores and Airbnb listing prices (Porges ,2013), however research on Airbnb listing prices in tourist spots is scarce (Wang and Nicolau, 2017).

Hence, there is a literature gap on tourist spots and price determination of Airbnb listing, especially when its focused-on Amsterdam. Gutiérrez et al. (2017), suggests that 'tourists tend to stay in places close to areas where the main sights and other tourist attractions are situated'. Therefore, research is needed to test this relationship if tourists are willing to pay more for an Airbnb accommodation that is located near tourist spots.

This research aims to build on existing literature to better understand the price determinants of Airbnb listing prices in Amsterdam. More specifically, it aims to investigate the geographical and locative parameters of tourist spots as price determinants of Airbnb listing prices since they are likely to be factors that influence Airbnb prices. Therefore, the following research question and sub-questions has been formulated:

RSQ: What is the association between the distance to tourist spots and Airbnb listing prices in Amsterdam?

For answering the research question, three sub-questions are formulated:

Sub-question 1: What are the determinants for Airbnb listing prices according to the academic literature?

Sub-question 2: What is the relationship between distance to the nearest tourist spot and Airbnb listing prices per night?

Sub-question 3: How does the relationship differ between low segment and high segment apartments?

To answer the research question and sub-research questions, an open dataset will be used for the Airbnb listing's and will be combined with ten selected tourist hot spots. A geographical information system has been applied to combine the tourist spots and Airbnb data. After multiple analyses in Arc(GIS), the dataset is transferred to Stata through which different regression analyses have been made.

This study contributes in the following way to the current literature. It will try to investigate the association between distance to tourist spots and Airbnb listing prices in Amsterdam. Moreover, the distribution of prices in the city center area is not evenly distributed, which can indicate different preferences of different segments of renters and therefore needs further investigation. This can play an essential role in creating fair prices and guarantee the economic sustainability of neighborhoods (Zhang et al., 2017).

The paper is structured as follows. The next chapter discusses the background of Airbnb and Locations. Chapter 3 will address the methodology, including obstacles identified in this research. Chapter 4 elaborates on the analysis and a discussion of the summary statistics. Chapter 5 will address the outcomes, implications and future research recommendations to the real estate market. The last chapter concludes on the findings.

2. Background information and Theoretical Framework

In order to investigate and answer the main research question, the previous literature and its underlying theories will be discussed. The subjects that will be discussed are Airbnb background information & spillover effects, Airbnb price determination, locations & amenities, and external markets & segments. After that, two hypotheses will be tested.

2.1 Airbnb background information & spillover effects

To gain a better understanding of the rapid growth of Airbnb all over the world, first the history and birth of the company must be discussed. The company Airbnb was founded in 2008 by Joe Gebbia, Brian Chesky, and Nathan Blecharczyk in 2008, and is based in San Francisco, California. The concept of Airbnb was born from installing air mattresses in their living rooms and turning them into a bed and breakfast. This expanded rapidly into renting properties including entire homes and apartments, private rooms. After one year of the launch in 2008, they already had 10.000 users and 2500 listings. Growth went exponential, and by June 2012 they had already passed 10 million bookings (Airbnb, 2020). As

mentioned earlier, Airbnb is operating in more than 100,000 cities across 220 countries, and with 7 million listings worldwide, it has rented to 500 million guests (Airbnb, 2020).

There are some spillover effects that need to be considered. As mentioned, increase in tourism creates both negative and positive spillover effects. Positive spillovers are improving the local economy (Perdue et al., 1990). On the contrary, negative spillover effects are an increase in the cost of living for residents (Woo et al., 2015) and increases social tensions and crime (Balaban, 2012). Therefore, more restrictions for cities are needed to protect the citizens and secure livability. Amsterdam has put restrictions on Airbnb listing. The new law only allows 30 days of renting each year, although sometimes the municipality allows to give you more days of renting. Besides, the renter needs a permit. Mostly, this is outside the city core (Airbnb, 2020). Unlike private vacation rentals, Bed & Breakfast has no days' limit and allows the renter to rent it all year. The big difference is that the renter must be the main resident of a home and rent out a room in your home. Therefore, Airbnb listing activity in Amsterdam remains high (Airbnb, 2020).

2.2 Airbnb price determination

As mentioned in the introduction, the 21st century can be characterized as the beginning of the sharing economy. People prefer renting above buying, which partly explains the rising popularity of Airbnb. Therefore, many researchers are investigating the preferences of Airbnb renters. According to the founders of Airbnb, renters experience a deeper connection to the communities they visit and the people who live there (Airbnb, 2020). Airbnb has built an online reputation system that gives guests and hosts the ability to rate and review each completed stay, to build trust and maximize the likelihood of a successful booking. Therefore, reviews and host listing count are an essential part of the price determination of Airbnb listing (Wang and Nicolau (2017). Host listing's count indicates how many Airbnb listings a rental has.

An important note can be made. Hotels are dependent on urban planning, which is not the case for Airbnb listing (Coles et al., 2018). Airbnb provides accommodations to visitors in areas that would otherwise have been infeasible. Therefore, Airbnb has a competitive advantage. For investigating the price determinants, the hotel price determinants can be used. These are, according to Wang and Nicolau (2017): site-specific characteristics, quality-signaling factors, hotel services and amenities, accommodation specification, and external market factors. Site-specific characteristics are actually the specified unique location, for example, the distance to the city center or tourist spots. This topic will be further enlightened in the next sub-section, 'Location and Amenities'. Quality signaling is the customer rating and stars for a hotel. By applying this to Airbnb, these are host listing count and reviews. Hotel services are the room amenities, like television or type of room. This can also be linked to Airbnb. There are shared rooms, private rooms, and entire homes. Accommodations specification are for example the car parking of fitness. This is actually not the case for Airbnb. Furthermore, these are specific variables and have less influence on the price (Monty et al., 2003); moreover, the results show that there are no

relationships between price and specific attributes for Bed and Breakfast. The last variable is external market factors. This is about the competition in the market. This will further be explained in the next sub-section, 'External market and Segments'. All these price determinants from hotels will be used for this research, except the accommodation specification. These are the most important price determinants of Airbnb listing, according to Wang and Nicolau (2017), who have analyzed the different price determinants for Airbnb listings. Moreover, they concluded that location is the most important part of price determination, but a good reason is missing. The next sub-section, 'Locations and Amenities' will enlighten this further.

2.3 Locations & amenities

As clarified earlier, rental incomes are associated with house prices (Manganelli et al., 2014). To clarify, it is interesting to look at the capitalization rate, which is associated with rental income and the purchase price of the property. Therefore, the relationship between rental income and house prices.

Nowadays, short rental is becoming more popular because of the attendance of Airbnb. Higher revenue can be obtained and therefore the house prices increase. This is confirmed by the research of Bijl (2016) who found an increase in Amsterdam of 0,42 percent. Moreover, the Dutch bank ING (2016), argues that a mortgage of around 100.000 euros extra can be obtained if the homeowner is renting for Airbnb.

A link can be made to the real estate world. To better understand the importance of locations, an old theory can be applied, namely the Bid rent model Alonso (1964). The bid-rent theory describes the outcome of land use and the resultant price by considering the perspectives of landowners and bidders. Bidders want the most favorable locations while the landowners want to rent to the highest bidder. A cautious link can be made here to Airbnb. The interest of tourists is mostly interested in amenities, and the price factor is becoming less influential (Goree, 2016).

It is clear that locations play a big role in the price determination of Airbnb listing. More than 85% of people choose Airbnb because of the attendance of amenities (Wang and Nicolau, 2017). Wang and Nicolau (2017) discuss and analyze the internal amenities, which is mentioned earlier in the price determinants of Airbnb listing. The internal amenities can be the minibar, flat-screen television, pool, fitness center, function space, lounge, spa, function space, room service, and valet parking (Lee et al., 2012). In other words, the internal amenities are adding extra value to a unique accommodation. External amenities are amenities that are available for everyone, which is not directly contributed to the accommodation.

Nowadays, it is also essential to understand the external amenities because there is a lack of data, and each city must be treated differently due to its unique amenities. Many studies have shown that amenities have a measurable and statistically significant impact on house prices (Quigley, 1982). The interpretation of these results reflects their choices, and it enables the researcher to derive the willingness-to-pay for housing or neighborhood attributes. This is, of course, measured on the housing

market, but a few studies have only looked at the external amenities and Airbnb prices (Wang and Nicolau, 2017).

Most tourists seek hotels that are within walking distance of attractive touristic areas spots in the city (Arbel and Pizam, 1977). An explanation can be that the average room rate is in the city center higher than outside the city center. Apparently, the location plays a big role in the rating of the average room rate, and therefore people are willing to pay more for a room (Gutiérrez et al., 2017). Tourist spots may affect the prices of Airbnb and tourists tend to stay in places close to areas where tourist spots are situated. Length of stay and number of previous visits to the city were found to have a substantial effect on visiting tourist spots. This might suggest that tourist, due to the limited amount of visiting time, wish to rent an Airbnb in close proximity to tourist spot. However, this is not yet been confirmed by the current literature.

Other studies researched the impact of the distance from the city center on prices but have not investigated where the tourist spots are and their role in it (Porges, 2013). The city of Amsterdam has different tourist spots and is not concentrated in the city center (Instasights, 2020). Wang and Nicolau (2017) are arguing that it is yet unclear what the impact is of location on the price of Airbnb listing. Therefore, further investigation and research is needed to uncover if there is a relationship between tourist spots and Airbnb listing prices.

2.4 External market & Segments

Customer segments are also key in understanding price differences. In a novel study by Hajibaba and Dolnicar (2018), who focused on the Slovenian hotel industry during 2010-2015, it was found that hotels that target low/medium consumer segments tend to set lower prices in cities where Airbnb has a higher market share (Hajibaba and Dolnicar 2018). However, it remains to be seen if this is also true for cities in other countries.

Hotel chains claim that Airbnb targets different segments (Tsang, 2017). This argument can be tackled by Guttentag and Smith (2017). In contrast, Guttentag and Smith (2017), are arguing that nearly two-third of Airbnb guests are hotel substitutes. This seems to indicate that there are customers across different segments that prefer Airbnb above Hotels. Moreover, Lutz and Nieuwlands(2018) find out that customers in different segments are interested in different types of rooms. The higher segment prefers private rooms; in contrast, the lower segment likes shared rooms more.

Furthermore, segmentation may not only imply that there are different segments of the rich and poor, but they may also help to develop a group-specific value for Airbnb. Airbnb renters, which they rent out their apartments, can be aware of the fact that if they set a high price, what kind of attributes they have to add a fair price. Besides, builders can develop houses or rooms that would fit the perceived needs of the group. Therefore, this research will investigate the different segments of Airbnb renters. In addition, Perez-Sanchez, et al. (2018) did a case study about 4 Spanish Mediterranean arc cities, and they find out that the higher segment of Airbnb renters is willing to pay more for their prices if the

location is near a tourist spot within 1 km, compared to the lower segment of Airbnb renters. To clarify, the higher segment will be accounted as above bound of the median price of an Airbnb price, and for the lower segment, the lower bound of the median price will be accounted. Further explanation in the Main empirical methods.

The following two hypotheses will therefore be tested:

H1: Closer access to touristic spots is positively associated with Airbnb listing prices per night.

H2: The prices per night of lower segment Airbnb listings is less sensitive to the distance of tourist spots than the higher segment.

3. Data & Methodology

3.1 Study area

Amsterdam has approximately 890.000 citizens and has almost every year 16 million day trippers(2019, CBS). Therefore, Amsterdam is one of the most popular tourist destinations in Europe. Moreover, Schiphol airport is the third-largest airport in Europe and is an import hub for Europe and the rest of the world. Also, Amsterdam can be characterized as an important player in the music world. Amsterdam Dance Event (ADE), attracts over 350.000 visitors each year. Furthermore, other big dance and festivals attract people from all over the world and make Amsterdam the ‘dance capital’ of the world.

As mentioned earlier, this research will try to explain geographical and locative tourist spot parameters for Airbnb listing prices in Amsterdam. It will focus on the urban area since that is the most interesting part of the research and tourists are most interested in.

3.2 Identifying attractive touristic areas

As mentioned earlier, tourist spots may affect the prices of Airbnb and tourists tend to stay in places close to areas where tourist spots are situated (Gutiérrez et al., 2017). Length of stay and number of previous visits to the city were found to have a substantial effect on visiting tourist spots. Previous data about the characteristics of a tourist is not available, but the average stay is available. Airbnb renters stay on average 3.9 nights in Amsterdam (CBS, 2019). This might suggest that tourist, due to the limited amount of visiting time, wish to rent an Airbnb in close proximity to tourist spot. However, this is not yet been confirmed by the current literature. In order to identify measurable tourist spots this research will look at two common tourist spots: parks and museums.

Public transport is left out in this research since this research is concentrated on city centers. Although public transport is important for urban areas, it is less so for city centers which are usually

well connected (Fang et al., 2019). People will go for a walk easier because of sightseeing. Therefore, this study will exclude public transport for research.

Data from the well-known travelling company Tripadvisor will be used to identify the tourist spots. This data will be further enriched with data from 'Instasights' which is a website that plots in heating layers where tourist spots are. When those layers are combined on a heat map is obtained that will show the tourist spots. From the heat map it is then possible to extract the top 10 tourist spots for the most important amenities determination. After adding more tourist spots, the heatmaps and Tripadvisor places are not covered well. This can indicate the less importance of the tourist sites. Furthermore, adding more touristic spots can lead to a less valid outcome (Gutiérrez et al., 2017). The heat maps can be found in appendix 1. These tourist spots are considered as relevant variables for the definition of Airbnb price determinants.

The study of Gutiérrez et al., (2017), are using 11 spots. Other studies are using the same method Cro and Martins, (2018); they are using 13 touristic spots.

The top 10 tourist spots in Amsterdam (Tripadvisor, 2020) are Rijksmuseum, Anne Frank House, Van Gogh museum, The Jordaan Area, Amsterdam Lookout, Body Worlds, Vondelpark, Moco Museum, Museum Het Rembrandthuis and Artis Zoo. Some studies identified fewer tourist spots, but this research will identify more because the layers of Instasight are better represented. The layer sightseeing also indicates the importance of Artis Zoo, which has 1.4 million visitors each year (Statista, 2019).

3.3 Airbnb Data

This research is using the open data source from Inside Airbnb which is a third-party website that identifies the number of reviews. An important note must be made, this is a non-commercial website, which makes it more reliable for use because there are no reasons to sabotage the data. This data is obtained in November 2020 and is cross-sectional data. Seasonality in the data is not a problem because Amsterdam has almost no differences in tourism flows (Ommeren et al, 2017). According to this study, and not looking at the origins of visitors, it is striking that the composition of the visit hardly deviates from an average day in Amsterdam. There is the only difference in the popularity of different nationalities. For example, English people seem to visit Amsterdam more in the summer period.

This dataset obtains many variables, namely: id number, name, host id, hostname, neighborhood, latitude, longitude, room type, price, number of nights, number of reviews, last review, reviews per month. To clarify, the latitude and longitude are not precise, it can have a distance variation of 150 meter from the original address. The reason is to protect the Airbnb identifications.

First, neighborhoods that are outside the city center, i.e. located outside the ring A10, have been removed. The official city center is located more in the center. This research took approximately 3 km around the tourist spots. As mentioned earlier, tourists tend to stay in places within walking distance to the areas where the tourist spots are located.

This research aims to investigate whether or not tourist areas are the most important part of location price determination in city centers; therefore, only the city center area will be researched. This data contains values from 2012 till 2020. All years will be used because the amenities are not changed over time. The top 10 tourist spots have been in existence for over 10 years and hence included in the data.

Second, the dataset contains hotel room nights in the typology room types. Since this research will focus on Airbnb, the hotel room listing was deleted (99).

The dataset excludes outliers since it can lead to a less reliable outcome. Outliers are removed with the help of the boxplot method in Stata. Both the upper bound and lower bound outliers, the percentiles 0,01, are deleted from the dataset. After removing these listing's and missing or wrong values, 13804 listing's remain in the dataset.

3.4 Control variables selection

The independent variable of interest in this study is the location parameters of tourist spots. The dependent variable of interest is the price. It can be measured by the distance to the nearest tourist spots since the dataset provides the longitude and latitude for each listing. This is calculated by using buffer geometry in Arcgis. A further explanation will be at subhead 3.6 Main Empirical methods.

First, control variables need to be considered. Unfortunately, the data set is limited, therefore it will use similar methods that haven been applied by other academic articles. Hence, this research will select the attributes that are available from the dataset to get as close as possible to the most important price determination variables. These are housing attributes, like the type of room. First, the type of room will be set as a control variable. According to several studies, this is one of the main price determinations basic components (Chen and Xie, 2017;, Guttentag and Gretzel, 2017, Morton et al., 2018; Wang and Nicolau, 2017). The room types will be set as a dummy variable.

There are three different room types, entire home/apartment, private room, and shared room. Of course, the price will be higher if the renter rents an entire home instead of a shared room. This is confirmed by Falk et al., (2019). Entire home rentals lead to 30 to 40 percent higher rents. This variable can be accounted as a building characteristic.

Some studies will create their own super host variable by looking at the review scores. This variable can be characterized as an advertising variable. This dataset does not consist of the data of review scores, only the host listing counts and reviews per month. Therefore, the host listing count and reviews per month will be used as a control variable. Host listings count stands for the amount of different listing's. Wang and Nicolau (2017) reported a significant positive correlation between the price and host listing count. This was also confirmed by Li et al., (2019). One of the reasons can be that hosts with more listings are accounted as more reliable and therefore also charge higher prices. Reviews per month can indicate the popularity of listing. This is a host attribute. Therefore, this research will threaten the host listing's count and reviews per month as a control variable.

This study will treat the different neighborhood types for controlling the spatial dependence pricing for Airbnb listing variables. It may be the case that Airbnb listings tend to set lower prices in neighborhoods where Airbnb has a higher market share (Hajibaba and Dolnicar 2018). Therefore, for controlling the different neighborhood types, dummies variables are included. All the tourist spots that have been selected are in different neighborhoods. In total, there are 15 neighborhoods included in this research.

To summarize, the control variables are room type, host listing count, reviews per month. These attributes are for building characteristics, host attributes, and advertisement.

3.5 Descriptive statistics

The descriptive statistics are shown Table 1.

Table 1 Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Listing price per night	13804	152.037	85.852	37	520
Minumum nights of booking	13804	2.891	2.375	1	20
Number of reviews	13804	26.904	49.016	1	312
Host Listings count	13804	2.609	8.865	1	86
Neighborhood	13804	7.392	4.299	1	15
Log price	13804	4.893	.524	1.609	7.601
Reviews per month	13804	66.193	97.279	2	523
(D)Entire home	13804	.798	.402	0	1
(D)Shared room	13804	.007	.084	0	1
(D)Private room	13804	.192	.394	0	1
(D)Nearest Ts < 0,2 km	13804	.025	.155	0	1
(D)Nearest Ts < 0,4 km	13804	.083	.276	0	1
(D)Nearest Ts < 0,6 km	13804	.106	.308	0	1
(D)Nearest Ts < 0,8 km	13804	.117	.321	0	1
(D)Nearest Ts < 1 km	13804	.11	.313	0	1
(D)Nearest Ts < 1,5 km	13804	.178	.382	0	1
(D)Nearest Ts < 2 km	13804	.12	.325	0	1
(D)Nearest Ts < 2,5 km	13804	.071	.257	0	1
(D)Nearest Ts < 3 km	13804	.03	.17	0	1

Notes: Nearest Ts stands for Nearest tourist spots. (D) Are dummy variables. The reference categories consist of distance > 3 km to nearest tourist spots

The variables are defined as following (see for a more comprehensive list of variables appendix 2). The Price variable is about the price of Airbnb listing each day. The minimum number of nights indicates how many nights must be booked for a stay in an Airbnb listing. In Amsterdam, the mean minimum number of nights is 2,891. This indicates the short stay and is in line with the findings from the CBS(2019), which was 3,9 nights. The number of reviews stands for how many reviews Airbnb listing has. The number of reviews mean is 26,7, which indicates that most renters are not first-time renters. The host listings count is about how many times a host is accounted for. The Room type is about the different room types. This is a categorical variable and is later added as a dummy variable. There are three different room types considered. 79,8 percent of the rental is an Entire home rental. After that, 19,2 percent is a private room rental, and almost 0,07 percent is a shared room. Neighborhood variable indicates the different neighborhoods. There are 15 neighborhoods included. The nearest Ts spots variables are about how many listings are located in that specific area. The reference category is more than 3km away located from the nearest tourist spots. The reference category has in total 2.298 listings, which counts for 16 percent of the total listings. See appendix 1.

In Figure 1, all the 13804 Airbnb coordinates are integrated in ArcGIS.

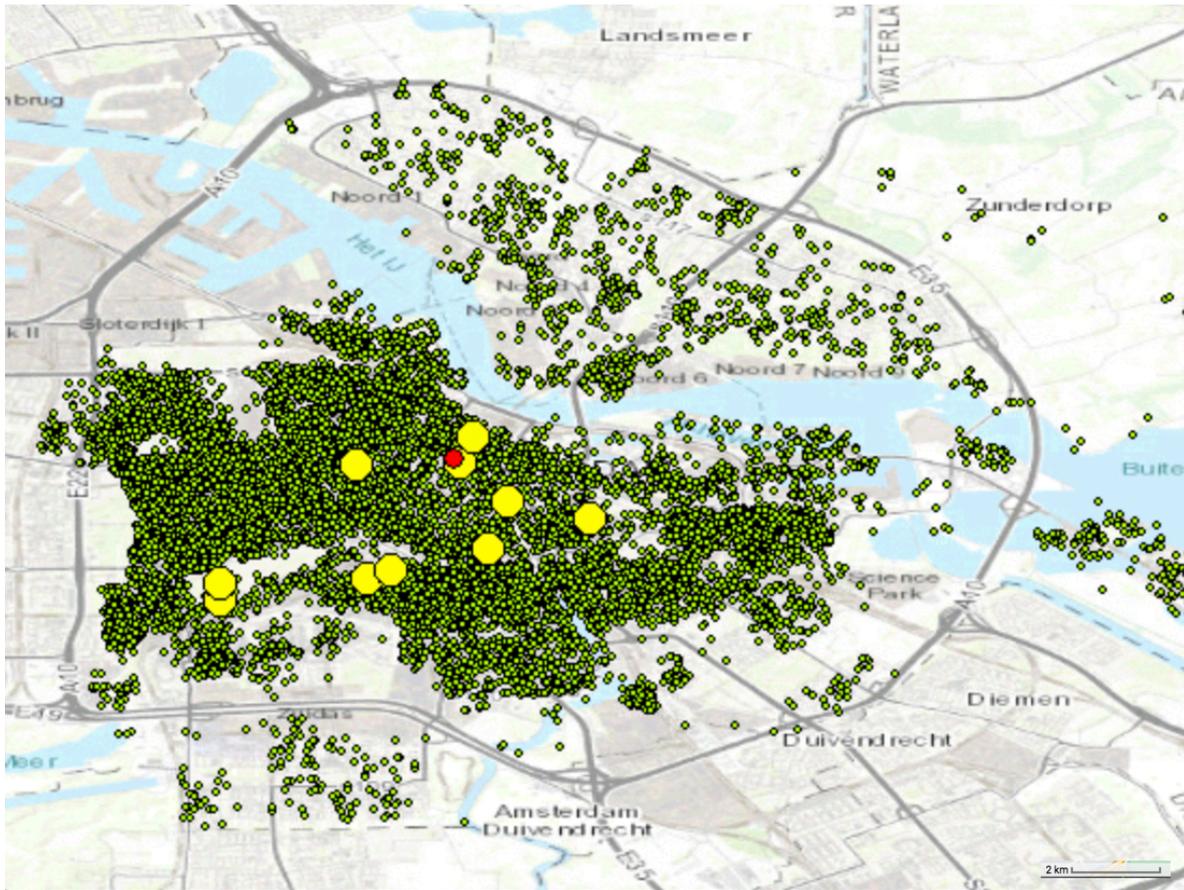


Figure 1: Airbnb listings in Amsterdam. Yellow dots are the different tourist spots & the red dot is the city center of Amsterdam (Damsquare)

3.6 Main Empirical methods

In this section, the main empirical methods will be discussed for the regressions. Dröes & Koster (2014) and Koster & Ommeren (2015), as do many other studies, use a hedonic regression model. This hedonic regression model uses the variable of interest, a selection of house characteristics, time, and location effect. These are the main independent variables for this research as well. Therefore, this study will also use the hedonic regression model. The hedonic pricing method is particularly useful for measuring the impact of specific elements on the value of goods or services through multiple regression analysis. In this way, the function of the price (P) that picks up each of the characteristics or elements can be expressed as the base model:

$$Price = f(B, H, A, L)$$

where P_i is the price of good i , and each of the f_i the characteristics defined with their corresponding regression coefficients. B stands for building characteristics, H stands for Host attribute, and A stands

for advertisement. L stands for the location. This is estimated by the ordinary least squares method (OLS).

Since the Price is the dependent variable, it is important that it is normally distributed in order to conduct a good analysis. Furthermore, Sirmans et al., (2005), indicate that Hedonic models are estimated with logarithmic forms. The main reason is to avoid heteroscedasticity and facilitating the interpretation of the coefficients. By transforming the log price, the Price is normally distributed and can be better interpreted by the different variables.

After applying Breusch-Pagan / Cook-Weisberg test for heteroscedasticity, it shows that the variance is not constant. Therefore, all the results are corrected with robust standard errors. These results can be found in the appendix 1.

After transforming the Price to a logarithm, the proposed equation for the baseline model of OLS model is the following:

$$\ln price = \beta_0 + \beta_1(\text{Hostlisteningscount}) + \beta_2(\text{Room Type}) + \beta_3(\text{Reviews per month}) + \beta_4(\text{Number of reviews}) + \beta_5(\text{Neighborhood}) + \varepsilon$$

Where Lnprice is the natural logarithm of the price of property. This is the dependent variable. It is transformed from Price to Lnprice. β_0 is the constant and β_1 -5 are the betas of the coefficients. $\beta_1(\text{Hostlisteningscount})$ stands for the coefficient that has to be estimated for the amount of host listings count. $\beta_2(\text{Room Type})$ is the coefficient of roomtype, which is in a dummy variable estimated. $\beta_3(\text{Reviews per month})$, stands for the coefficient of reviews each month in coefficients. $\beta_4(\text{Number of reviews})$ is the coefficient that needs to be estimated for the number of reviews. The last $\beta_5(\text{Neighborhood})$ variable, will be estimated with a dummy variable, for controlling the different neighborhood types. Finally, 'ε' represents the error term of the model which is assumed to be i.i.d. (see Appendix 1 for more details).

For adding tourist spots, a location dummy is added. This is estimated in the following equation empirically:

$$\ln price = \beta_0 + \beta_1(\text{Hostlisteningscount}) + \beta_2(\text{Room Type}) + \beta_3(\text{Reviews per month}) + \beta_4(\text{Number of reviews}) + \beta_5(\text{Neighborhood}) + \beta_6(\text{NearestTouristspots}) + \varepsilon$$

All other variables remain the same from the baseline model. The nearest tourist spots variable is treated as a dummy variable for controlling the variable. The different distances from 0-0,2 km; 0,2-0,4km;0,4;04-0,6km;0,6-08km;0,8-1km-1-1,5km;1,5-2km;2-2,5km;2,5-3km are considered in the

model as Nearest Tourist spot. This indicates how many Airbnb listings are in that specific area. If an Airbnb listing is located in that specific variable, it will be accounted as 1. See also appendix 2.

This research choice considers the spatial interaction between observations within a 1 km radius, that is, a typical 15-min walk. Moreover, more distances have been added to test if the tourist wants to walk more than 15 min. The longest distance is 2,5km - 3km. The reference category is more than 3km away located from the nearest tourist spots. The reference category has in total 2.298 listings.

The different distances are chosen because of the reason that most distances must be walkable for tourists (Carr et al., 2010). Therefore, the importance of walkability is important. Carr et al., (2010) confirm this, the higher the urban area density, the higher scores for walkable amenities. Since all the tourist spots are concentrated in urban areas, this should be an important factor to research.

This is measured by the method of applying buffers in the ArcGIS map. All the tourist spots that are located on the map will have buffers around them. The bigger the buffer, the more listings of Airbnb are in the radius. This all is converted to excel and afterward to Stata by hand. All the listings that are accounted for in the buffers are marked as a dummy variable. In total, there were 11.506 selected, in all buffers together.

3.7 Quantile regression

Because of the importance of understanding the value of tourist spots, a quantile regression has been added. This will lead better understanding of the different segments of tourists, tourists with less money to spend and tourists with more money to spend. Perez-Sanchez et al., (2018) defines that there are low and rich house households. This is also the case for Airbnb. Therefore, the same criteria will be used. This paper identifies the lower segments as poor, which is under the lower median price. This is under the 0,5 quantile of the median price. The rich quantile is the upper bound, namely above the 0,5 quantile of the median price. Moreover, other articles are using the quantile regression method(QRM) to better understand the variety of housing characteristics on prices (Zietz et al., 2008, Perez-Sanchez et al., 2018). The main advantage is that the dependent variable can be explained at any point of the distribution. In other words, it allows for identifying the shadow price component more, the unobserved heterogeneity. This is important for understanding the drivers since pricing is not normally distributed. OLS suggests that it is normally distributed, however this is not the case. A reason could be that different consumers may value housing characteristics in a different way. A simple OLS regression may not provide useful information for either price range since it is based on the mean of the entire price distribution. (Malpezzi, 2003). The lower segment of Airbnb is location amenities, perhaps more important because you only will sleep there. This relationship is yet unclear; therefore, this research will add a quantile regression for a better understanding of the value of amenities and different groups of Airbnb renters.

Before adding a quantile regression, the chow test will be performed (Brooks & Tsalacos (2010). A Chow test provides information about whether regression coefficient is different for the different

group samples. It fulfills two goals: First, it test the sensitivity and it may provide to answer the hypothesis.

The base line model for quantile regression can be expressed as:

$$Y_i = X_i\beta_i + U_i$$

Where Y_i is the dependent variable, which is the price of an Airbnb listing each day. X is the matrix of independent variables, where β is the vector of the parameters to be estimated for the specific quantile. These independent variables are the housing characteristics, values of interest and location. U_i is the vector of residual for the specific quantile.

The main difference between the hedonic model is that the quantile regression makes it possible to statistically examine the extent to which housing characteristics, values of interest and location effect are valued differently across the distribution of Airbnb prices. In other words, it does not take the median of each variable. Instead, it takes different quantiles of the variables. For example, in the 0,1 model, each variable is the 0,1-quantile taken.

The quantile regression will be conducted into 5 models, representatively: 0,1 quantile, 0,25 quantile, 0,5 quantile, 0,75 quantile and 0,9 quantile. By specifying multiple quantile regression lines, it makes it possible to gain a better understanding of the different preferences of the different segments of Airbnb prices. The median line in the quantile regression line, which is the 0,5 quantile, half of the data is above the line, and the other half of the data is under the line.

There may be some bias in the model. Therefore, standard errors of the coefficient estimates are estimated using the bootstrapping method. This is suggested by Gould (1997), especially if quantile regression is conducted. This is applied due to the concerns that the outliers influence the sampling distribution. According to Gould (1997), the bootstrap technique is a resampling technique used to estimate statistics on a population. It is sampling a dataset with replacement. A great advantage is its simplicity, and it can be easily conducted. It will derive the estimates of standard errors and confidence intervals, such as percentile points.

4. Empirical Results

4.1 The results of OLS regression

The main results of the OLS regressions are presented in Table 2. The standard errors are the robust standard errors, because of the heteroscedasticity problem. In addition, multicollinearity can induce the validation of the outcome (Mansfield et al., 1982). Therefore, the method variance inflation factor has been applied for if there is such a problem in multicollinearity. The outcomes of the VIF indicate there is no multicollinearity. The results can be found in Appendix 1, assumption 4.

Table 2 OLS regression

VARIABLES	(1) log_price	(2) log_price	(3) log_price
Host Listingscount	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)
Reviews per month	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Number of reviews	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
(D)Entire home	0.832*** (0.071)	0.836*** (0.070)	0.824*** (0.071)
(D)Shared room	0.411*** (0.084)	0.402*** (0.084)	0.405*** (0.084)
(D)Private room	0.269*** (0.071)	0.275*** (0.071)	0.271*** (0.071)
(D)Nearest Ts < 0,2 km		0.142*** (0.029)	0.265*** (0.027)
(D)Nearest Ts < 0,4 km		0.091*** (0.019)	0.191*** (0.017)
(D)Nearest Ts < 0,6 km		0.087*** (0.018)	0.149*** (0.015)
(D)Nearest Ts < 0,8 km		0.057*** (0.017)	0.093*** (0.015)
(D)Nearest Ts < 1 km		-0.000 (0.017)	0.023 (0.015)
(D)Nearest Ts < 1,5 km		-0.025 (0.015)	-0.028** (0.013)
(D)Nearest Ts < 2 km		-0.067*** (0.017)	-0.108*** (0.015)
(D)Nearest Ts < 2,5 km		-0.025 (0.020)	-0.099*** (0.017)
(D)Nearest Ts < 3 km		-0.036	-0.085***

		(0.027)	(0.024)
Neighborhood dummies	Yes	Yes	No
Constant	3.988***	4.020***	4.183***
	(0.072)	(0.073)	(0.072)
Observations	13,804	13,804	13,804
R-squared	0.262	0.269	0.252

Notes: Nearest Ts stands for Nearest tourist spots. (D) Are dummy variables. The reference categories consist of distance > 3 km to nearest tourist spots
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

By comparing the three models, the pooled model with Neighborhood dummies illustrates a greater R-squared, model 2. This indicates that the pooled model 2 is a better model due to a higher explanatory power. Furthermore, leaving neighborhood dummies out of the model will lower the R-squared.

Starting at the baseline model, the R-squared is 0,262, which means that the model explains 26,2 percent of the variance of the listing's price of an Airbnb. As expected, all the variables in the baseline model are significant at the highest level and influence the listing's price of an Airbnb. In the first model, neighborhood dummies are included for controlling the space.

The room type outcomes shows that entire homes are more expensive than private rooms. This is confirmed by all the models. The Baseline model significance coefficients are in line with the findings of Wang and Nicolau,(2017). They showed the same findings and significance levels. For example, the host listings count coefficient in the OLS regression is 0,004, with the highest level of significance. In this OLS regression, almost the same findings are presented. Furthermore, the Entire home results from Wang and Nicolau,(2017), shows almost the same coefficients. They estimated in their model 0.8948, with the highest level of significance.

The Pooled model 2 and model 3, by adding the variables Nearest tourist spots from 0,2 km till 3km, showed that if the nearest tourist spots are located further than 1 km away, prices will drop. The reference group is more than 3km away located from the nearest tourist spots.

Thus it has a negative impact. Model 2 with The Nearest tourist spots 1km and Nearest tourist spots 1,5 km, are not significant, which indicates that the relationship is not clear. For model 3, the Nearest tourist spots 1,5 km are significant at the 5% level.

All the other findings are significant.

4.2 Quantile regressions results

There is also some criticism when it comes to the OLS model. As mentioned earlier, it is important to understand the different drivers of different customer segments. Since the market is heterogeneous, the OLS is less powerful for understanding the price distribution, even when robust errors are applied into the OLS regression. The price distribution is not normally distributed, and therefore, a quantile regression will be conducted. Moreover, a Chow test has been conducted and confirmed that the parameters are not stable over time (appendix 2). Therefore, this thesis has focused on one type of room, which is entire homes, since this is the biggest group of interest. In table 3, the results are displayed. As mentioned earlier, bootstrapping (Gould, 1997), is applied on all the results.

Table 3 Quantile Regression Entire homes

	(1)	(2)	(3)	(4)	(5)
	model 1 QR	model 2 QR	model 3 QR	model 3 QR	model 3 QR
	0,1	0,25	0,5	0,75	0,9
VARIABLES					
Host Listings count	0.004*** (0.001)	0.005*** (0.001)	0.005*** (0.000)	0.004*** (0.001)	0.005*** (0.001)
Reviews per month	-0.001*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)
Number of reviews	0.001*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	-0.000*** (0.000)
(D)Nearest Ts < 0,2 km	0.072* (0.039)	0.135*** (0.044)	0.182*** (0.049)	0.261*** (0.047)	0.273*** (0.083)
(D)Nearest Ts < 0,4 km	0.075** (0.034)	0.105*** (0.026)	0.114*** (0.031)	0.118*** (0.037)	0.100** (0.043)
(D)Nearest Ts < 0,6 km	0.055*** (0.017)	0.098*** (0.021)	0.077*** (0.022)	0.105*** (0.037)	0.106*** (0.041)
(D)Nearest Ts < 0,8 km	0.060***	0.078***	0.054**	0.060**	0.017***

	(0.019)	(0.019)	(0.021)	(0.026)	(0.037)
(D)Nearest Ts < 1 km	0.022	0.012	0.010	0.000	0.007
	(0.030)	(0.018)	(0.022)	(0.029)	(0.038)
(D)Nearest Ts < 1,5 km	0.010	-0.013	-0.024	-0.034	-0.036
	(0.027)	(0.023)	(0.021)	(0.025)	(0.032)
(D)Nearest Ts < 2 km	-0.028	-0.054***	-0.068***	-0.053***	-0.050
	(0.019)	(0.016)	(0.021)	(0.018)	(0.036)
(D)Nearest Ts < 2,5 km	0.006	-0.012	-0.036*	-0.033	-0.051*
	(0.025)	(0.021)	(0.021)	(0.023)	(0.029)
(D)Nearest Ts < 3 km	-0.098**	-0.106***	-0.126***	-0.058***	-0.019***
	(0.038)	(0.037)	(0.034)	(0.054)	(0.079)
Constant	4.430***	4.610***	4.835***	5.063***	5.324***
	(0.021)	(0.024)	(0.026)	(0.020)	(0.038)
Neighborhood dummies	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.283	0.316	0.360	0.372	0.361
Observations	11,010	11,010	11,010	11,010	11,010

Notes: Nearest Ts stands for Nearest tourist spots. (D) Are dummy variables. The reference categories consist of distance > 3 km to nearest tourist spots

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The results show that especially the lower market segment (0,1 quantile) is less sensitive to the Nearest tourist spots. This indicates that Airbnb renters with a low budget are less interested in the nearest Tourist spots and prefer walking or biking, for example. The results show that the Nearest tourist spots of 2,5km distance have a higher value than for the higher segment (0,75 quantile and 0,9 quantile).

The lower segment (0,1 quantile and 0,25 quantile) is less sensitive for Tourist spots than the higher segments overall, especially if the nearest tourist spots are less than 0,2 km distance.

The middle segment of the quantile (0,5), is also sensitive to locations. After 1 km nearest tourist spot, there is a negative coefficient, which indicates that there the prices will drop. But the results between 0,8km and 2km nearest tourist spots are not significant. The outcome Nearest tourist spots from

2km till Nearest tourist spots 3km are significant. This indicate that prices will drop if the nearest tourist spots are located further away than 2km.

What is in common for all segments is that the tourist spots are located further away than 1 km, they will have negative coefficient's and the results are not significant anymore. This indicates how important the location is, and prices will drop if the location is located further away than 1 km.

The Pseudo R-squared indicates that if the higher the price segment, the better the model is a good explanatory model (Koenker and Machado, 1999). A pseudo R-squared of a 0.2 minimum is required for a good model fit (Koenker and Machado, 1999). Probably, this can indicate the lower segment prefers other amenities as well. Nevertheless, the outcomes are not beneath a Pseudo R-squared of 0,2.

5. Discussion

This research adds to the current debate extra information of the location factors, focusing on the tourists' spots in Amsterdam. The growing importance of understanding the different drivers is more important than ever nowadays. If the tourism flow is well managed, positive results related to urban sustainability can be obtained such as local and tourist interaction, lower vacancy rates and increased livability (Porges, 2013).

It is not only for policymakers important for understanding the drivers but also for Airbnb renters and Airbnb hosts. The results show, looking at Model 2 of the OLS regression, that when the nearest tourist spots are between 2,5 and 3km away, prices drop by 3,6 percent of listing of Airbnb prices. Furthermore, the quantile regression puts a different view on the higher segments renters and lower segments renters. For renters that aim at the higher segment, it means that the location is an essential determinant in the rental price. People are willing to pay for a good location. Also, the lower segment likes to walk or travel to the nearest tourist spots; they are less sensitive to a good location, which sounds logical. In contrast, this phenomenal is not confirmed by Perez-Sanchez et al., (2018). This study is about 4 Spanish Mediterranean arc cities and the location price determination of Airbnb, selected as a case study. Their results show that the closer to tourist areas, the lower the price by 1.3 percent per kilometer. In addition, they did also research about the coast distance to an Airbnb listing; they found out that the rental decreased per kilometer by 2.7 percent. It may indicate that when people are going to southern cities with beaches, people tend to prefer beaches above tourist spots. In Amsterdam, there are no beaches, only recreation parks, which obviously, is something different. Therefore, this study can add new findings that southern European cities cannot be treated the same as northern European cities. As for future research, it may be interesting to look at other northern cities if this phenomenon can be confirmed.

What is in common with the paper of Perez-Sanchez et al., (2018), especially in the higher segment, is the willingness to pay higher prices for Airbnb near tourist spot that are within 1 km. Their quantile regression shows that the higher segment wants more to go sightseeing and shopping. It might be also the case for the higher segment in Amsterdam. Future research can aim more on the higher segment and add more variables into the model.

An important implication for new Airbnb renters outside the nearest tourist spots can be that people are willing to pay less but are not afraid to walk or travel a bit more. For spreading the Airbnb density, it can be important for policymakers to decide the accessibility of walking and other facilities that can make transport easier. This is mainly because the OLS regression shows that people will pay less after a 1.5km radius to the nearest tourist spots. Also, a suggestion can be to invest or relocate tourist spots in an area, such as building a museum in a neighborhood or creating good parks. This can of course, also increase the livability in a neighborhood. As mentioned earlier, amenities can increase the attractiveness of a neighborhood. Moreover, a museum-like ‘Body worlds,’ which is in the middle of the center, could also be placed somewhere else. This will also improve the flows of tourists as the center of Amsterdam is already flooded with tourists. Relocating museums outside the city center could ease the pressure on the city center caused by these tourist flows. Add the same time, relocating to other neighborhoods could increase livability in these neighborhood as they might profit from tourism. Further research should aim more on the problem of mass tourism in the city of Amsterdam and how to make Amsterdam more sustainable over time.

Another finding is that the results show that the highest quantile is willing to pay more for a good location and premium room, which is an entire home. (Wang and Nicolau, 2017), showing the same results. These results can be linked to the urban rent theory from Alonso (1964), because the bidders want the most favorable locations while the landowners want to rent to the highest bidder. An option for policymakers is to spread out the Airbnb listings over the city is by putting a roof price for Airbnb listings. This makes it less interesting for landowners to rent out their apartments. A recent study shows by Vandrei, (2018), that apartment sales will be reduced by 20-30 percent. This can increase livability and can reduce the overheated housing market. This study was conducted in Germany, in the state of Brandenburg. Vandrei, (2018) compared the sales prices in municipalities that are located marginally above with those slightly below marginally prices. It may be a solution for Dutch policymakers to tackle this problem in Amsterdam since Airbnb will affect house prices as well. As mentioned earlier, Airbnb is driving up the housing prices in the residential real estate market (Gallin, et al., 2006).

In addition, a note must be made for the regression. There are no other location factors integrated into the model and therefore may be overestimated in the model or underestimated. Other typical location variables in Amsterdam can be important. To give an example, a coffee shop location. It might be the case that this some tourist look for an accommodation that is closely located at a Coffeeshop. Moreover, 16 percent of the tourism of Amsterdam is a drug tourist (Trouw, 2021). The location of an

Airbnb and the location of the nearest coffee shop may be important price factors. This needs further research for the Airbnb market.

6. Conclusion

Locations have an important role in price determinations of Airbnb listings. Moreover, it can be concluded that there is a distance effect on tourist spots in the price determination of Airbnb listings. The most significant finding is that tourist spots have an important factor in the price determination of Airbnb, especially in areas between 0,2 km and 1 km. Tourists are willing to pay more for an Airbnb that is closely located to a tourist spot. There are differences between the higher segment preferences and lower segment preferences by looking at apartment's rental. The lower segment is less sensitive to locational distance effect compared to the higher segment of the Apartments rental. The results of this study are useful for policymakers in Amsterdam to understand the spatial pattern of Airbnb. By understanding the importance of amenities, Amsterdam can increase its livability and can create a sustainable future for the city. This study has focused on the locative parameters of tourist spots in the center Amsterdam. Therefore, future research could focus more on suburbs of Amsterdam by investigating other potential relevant locational variables, like cafes or restaurants.

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Appendix 1

Assumption 1

OLS assumptions

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance

Variables: log_price

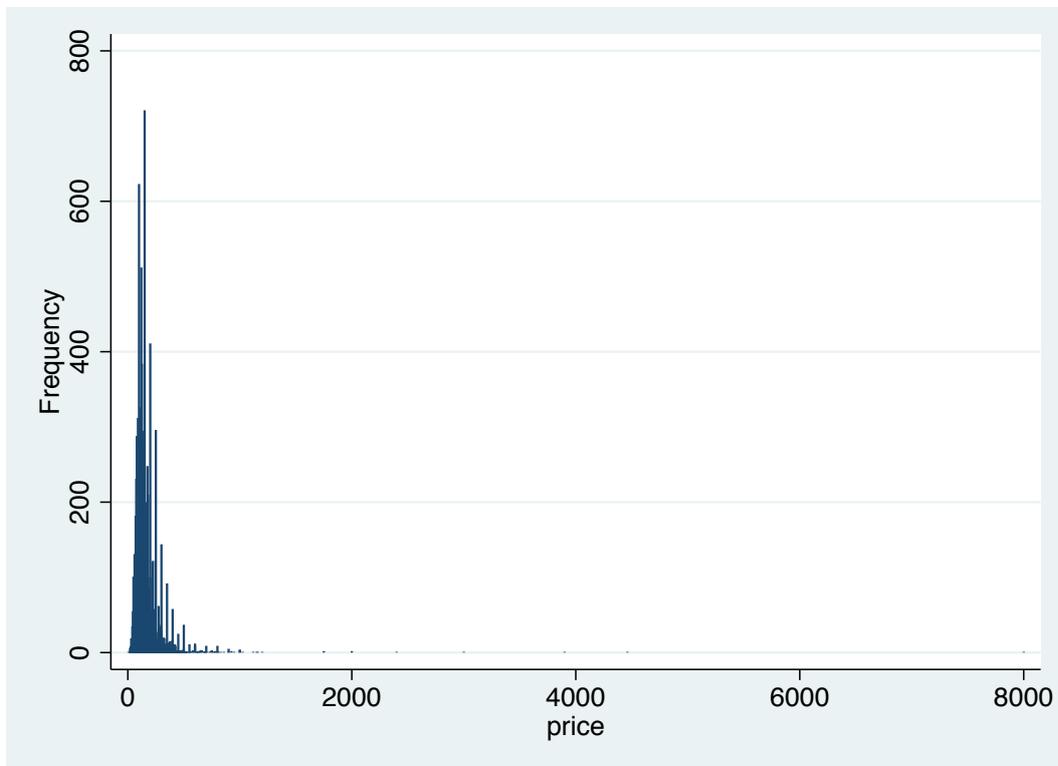
chi2(1) = 2240.18

Prob > chi2 = 0.0000

Because of the P value is below 0,05(0,00), robust standards errors are used for the OLS model. This implies that there is not a constant error of the variance. By adding robust standard errors can make it more reliable for use.

Assumption 2

Price distribution is not normal distributed. Because of this, outliers have been removed, from the 1 percentage tail from both sides.



Assumption 3

The heatmap of Instasights



Assumption 4

Outside the buffer rings, the reference category located.



Assumption 5

No multicollinearity exists among the independent variables.

VIF autocorrelation method has been applied. According to Mansfield, E.R. and Helms, B.P., (1982), values above 10 are not allowed. If all the variables (inclusive dummies) are integrated in the model, multicollinearity is not found.

Variance inflation factor

	VIF	1/VIF
HostListingscount	1.005	.995
reviewsmoonth	1.322	.756
3.roomtype	1.292	.774
4.roomtype	1.006	.994
2.Hood	1.216	.822
3.Hood	3.129	.32
4.Hood	3.737	.268
5.Hood	4.365	.229
6.Hood	3.446	.29
7.Hood	1.672	.598
8.Hood	1.38	.724
9.Hood	1.575	.635
10.Hood	1.782	.561
11.Hood	1.534	.652
12.Hood	2.544	.393
13.Hood	1.443	.693
14.Hood	2.496	.401
15.Hood	2.669	.375
Nearest02TS	1.34	.746
Nearest04TS	1.929	.518
Nearest06TS	1.998	.5
Nearest08TS	2.042	.49
Nearest1TS	1.989	.503
Nearest15TS	2.411	.415
Nearest2TS	2.062	.485
Nearest25TS	1.861	.537
Nearest3TS	1.454	.688
Mean VIF	2.026	.

Appendix 2

Table variables descriptions

The first column indicates the variable name. The Second column gives a short description of the function and calculation. The third column is the source.

Variable name	Description	Source
Min number of nights	The minimum number of nights that needs to be booked for the Airbnb accommodation.	InsideAirbnb (2020)
Number_of reviews	The number of reviews about the Airbnb accommodation	InsideAirbnb (2020)
Host Listing's count	Host listing's count indicates how many Airbnb listings a rental has.	InsideAirbnb (2020)
Roomtype	The Roomtype is about the different room types. This is a categorical variable and is treated as dummy variable	InsideAirbnb (2020)
Neighborhood	Neighborhood variable indicates the different neighborhoods. Accounted as dummy variable	InsideAirbnb (2020)
log_price	This is the logarithm of price	InsideAirbnb (2020)
Reviewsmonth	This variable indicates how many reviews a host will receive each month	InsideAirbnb (2020)
Entire home	This is a dummy variable from the Roomtype. This indicates that a the entire home is rented. (If yes = 1)	InsideAirbnb (2020)
Shared room	This is a dummy variable from the Roomtype. This indicates that it is a shared room. (If yes = 1)	InsideAirbnb (2020)

Private room	This is a dummy variable from the Roomtype. This indicates that it is a private room. (If yes = 1)	InsideAirbnb (2020)
Nearest Ts < 0,2 km	If the Nearest Tourist spots are located between 0 till 0,2 km from Airbnb accommodation, accounted as a dummy variable. (If yes = 1)	Tripsadvisor & Instasights (2020)
Nearest Ts < 0,4 km	If the Nearest Tourist spots are located between 0,2 till 0,4 km from Airbnb accommodation, accounted as a dummy variable. (If yes = 1)	Tripsadvisor & Instasights (2020)
Nearest Ts < 0,6 km	If the Nearest Tourist spots are located between 0,4 till 0,6 km from Airbnb accommodation, accounted as a dummy variable. (If yes = 1)	Tripsadvisor & Instasights (2020)
Nearest Ts < 0,8 km	If the Nearest Tourist spots are located between 0,6 till 0,8 km from Airbnb accommodation, accounted as a dummy variable. (If yes = 1)	Tripsadvisor & Instasights (2020)
Nearest Ts < 1 km	If the Nearest Tourist spots are located between 0,8 till 1 km from Airbnb accommodation, accounted as a dummy variable. (If yes = 1)	Tripsadvisor & Instasights (2020)
Nearest Ts < 1,5 km	If the Nearest Tourist spots are located between 1 till 1,5	Tripsadvisor & Instasights (2020)

	km from Airbnb accommodation, accounted as a dummy variable. (If yes = 1)	
Nearest Ts < 2 km	If the Nearest Tourist spots are located between 1,5 till 2 km from Airbnb accommodation, accounted as a dummy variable. (If yes = 1)	Tripsadvisor & Instasights (2020)
Nearest Ts < 2,5 km	If the Nearest Tourist spots are located between 2 till 2,5 km from Airbnb accommodation, accounted as a dummy variable. (If yes = 1)	Tripsadvisor & Instasights (2020)
Nearest Ts < 3 km	If the Nearest Tourist spots are located between 2,5 till 3 km from Airbnb accommodation, accounted as a dummy variable. (If yes = 1)	Tripsadvisor & Instasights (2020)

Appendix 3

Chow test

For testing if the groups can be taken together, a Chow test is conducted. The first Chowtest is applied on the different type of rooms. A second Chow test is applied on the higher and lower segment. A Chow test provides information about whether regression coefficient is different for the different group samples. It fulfills two goals: First, it test the sensitivity and it may provide to answer the hypothesis.

The Chow test is conducted in the way by Brooks & Tsalacos (2010). For the first part, the sum of the residuals in the three groups are collected by running separate regressions. Secondly, the various of sum of residuals are inserted in the test statistic. After that, the test statistics is compared to the F-distribution, to see if the null hypothesis is rejected. The null hypothesis say that there are no significant differences between the different sub-samples. The test statistic is calculated by:

$$Test\ Statistic = \frac{RSS - (RSS1 + RSS2 + RSS3) * \frac{T-3 * K}{3 * K - K}}{RSS1 + RSS2 + RSS3}$$

F = (2k-k, n-2k)

$$Test\ Statistic = \frac{2776.96564 - (2147.1902 + 29.1792614 + 522.831202) * 13804 - (3 * 28)}{2147.1902 + 29.1792614 + 522.831202} * \frac{13804 - (3 * 28)}{84 - 28} = 0,02881045 * 245 = 7,0585$$

$$F = (3 * 28) - 28, (13804 - (3 * 28))$$

$$F = 56, 13720 = 1.394 - 1.318$$

The test statistic is 7,0585, which is greater than the critical value from the F-distribution calculation. This indicates that the parameters are not stable over time.

Second, there is a chow test conducted on low vs. high listing prices of Airbnb. First the low listing prices group is identified. This is the group under 130 listing price. Everything above can be characterised as high listing price. The same calculation method of type rooms is applied here. For the first part, the sum of the residuals in the two groups are collected by running separate regressions. Secondly, the various of sum of residuals are inserted in the test statistic. After that, the test statistics is compared to the F-distribution, to see if the null hypothesis is rejected. The null hypothesis say that there are no significant differences between the different sub-samples. The test statistic is calculated by:

$$Test\ Statistic = \frac{RSS - (RSS1 + RSS2)}{RSS1 + RSS2} * \frac{T - 2 * K}{2 * K - K}$$

$$F = (2k - k, n - 2k)$$

$$Test\ Statistic = \frac{2776.96564 - (511.083282 + 812.972166) * 13804 - (2 * 28)}{511.083282 + 812.972166} * \frac{13804 - (2 * 28)}{56 - 28} = 1,097318235$$

$$* 491 = 538,7832536$$

$$F = (2 * 28) - 28, (13804 - (2 * 28))$$

$$F = 28, 13748 = 1,3832 - 1,3419$$

The test statistic is 538,7832, which is greater than the critical value from the F-distribution calculation. This indicates that the parameters are not stable over time.