Understanding the value of location in the Airbnb market

Evidence from Rome

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Abstract

This study explores how close access to attractive touristic areas are reflected into Airbnb listing prices in the urban environment by means of multiple hedonic price models. A proxy for the attractive touristic areas is generated using Instasights, which measures the popularity of places based on user-perceptions and TripAdvisor ratings. The findings show that attractive touristic areas are reflected into Airbnb listing prices up to 5 kilometers away from the nearest attractive touristic area. The magnitude of the positive effect diminish as the distance to the nearest attractive touristic area increases. In addition, this study shows that the relative internalizaton of attractive touristic areas into listing prices is larger for the lower priced market segmentation compared to the higher priced market segmentation. The findings of this study can inform tourism property investors and provide policy makers with an information baseline regarding how close Airbnb users wish to stay to attractive touristic areas

Keywords: Airbnb, Location quality, Market segmentation, Hedonic price models

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1.Introduction

The world is becoming increasingly urbanized. In 2030, urban areas will inhabit more than 65 percent of the of the world's population. These urban areas are currently generating more than 60 percent of the Global GDP and this share is expected to grow. An emerging economic force in many cities is urban tourism (UNWTO, 2018). Urban tourism is one of the fastest growing segments within tourism in developed countries as people tend to take shorter trips more often (Mason, 2005; Martin & Sentis, 2016; Maitland and Richie, 2009). Globally, the amount of urban trips has grown by 82 per cent and reached a market share of 22 per cent of all vacations in the period 2007-2014 (IPK International, 2015/2016, p. 8). Urban tourism is important in several ways as it promotes investments, stimulates foreign exchange through revenues and taxes and creates jobs for city and regions (UNWTO, 2018). Urban tourism distinguish itself from other types of tourism by travelling to places with a high population density and the time spent at the destination is usually shorter than the average stay on other vacation trips (Martinez & Raya, 2008). From a tourist perspective, the most important basic need at the destination is arguably an accommodation as a tourist always need a place to stay during their trip. Tourists visit cities for a short time period, therefore one of the main priorities in choosing an accommodation is the location (Lockyer, 2005; Barros & Machado, 2010). Tourists want to stay in accommodations in environments they appreciate for several reason such as proximity to coastline, key infrastructure nodes or natural aesthetics such as mountains and rivers. However, due to time restrictions, urban tourists tend to stay centrally and visit only the major main sights and want to locate at places, which are at walkable distance from such main sights (Arbel & Pizam, 1977; Barros & Machado, 2010; Gutierrez *et al*, 2017; Paldino *et al.*, 2015). In general, tourists think that walking as transport mode is the best way to experience a city (Thompson, 2003). How proximity to main touristic sites is valued by tourists is the subject of this study on the Airbnb market, which is particularly suited for this type of analysis as it may in theory cover cities in their entirety.

Airbnb arises as the largest business model to connect households who want to rent out their home with people who are seeking for a temporary property. Airbnb, founded in 2008 in San Francisco, has experienced enormous growth in the last decade resulting in a platform which facilities more than 7 million listings now (Airbnb Newsroom, 2020). The fundamental factors which explain the success of Airbnb, that tourists choose for Airbnb over a traditional accommodation, relates to the relatively low price, the unique locations and the interaction with the hosts (Guttentag *et al.*, 2015; Zhang *et al.*, 2017). Airbnb accommodations are mainly a substitute for traditional accommodations rather than attracting new tourism flows and these Airbnb listings are in particular attracting leisure travellers (Guttentag & Smith, 2017; Lutz & Nieuwlands, 2018). Airbnb listings can arise in existing residential areas, which make it more facile to locate on attractive locations for leisure travellers, such as close to main sights, compared to hotels which rely on zoning regulations, available space and development costs (Rogerson, 2014; Gutierrez *et al.*, 2017; Cro & Martins, 2018).

This research will, in specific, focus on how location quality of attractive touristic areas reflected into Airbnb listing prices in the urban environment. An attractive location is characterised by a higher customer satisfaction, therefore a larger demand and consequently higher listing prices (Lockyer, 2005). From these initial, real estate investors may be interested in the implicit value tourists attach to location quality which enables them to improve their investment decisions. On the other hand, insight in the impact of location in the Airbnb market provides policymakers with a good information baseline as higher prices for certain location are an indication that a relatively high pressure on the housing supply exist. As Airbnb supply in theory should follow price signals, it is likely that the supply of Airbnb will increase in attractive touristic areas. However, while location has often been a key factor in explaining prices in the accommodation sector, see Lockyer (2005), relatively few studies consider the impact of location on Airbnb prices.

Common urban economic theory dictates that, also in the accommodation sector and therefore the Airbnb market, a property in a favorable location, will have a higher listing price than a listing on a less favorable location (Alonso, 1960; Lockyer, 2005). Airbnb listings arise in existing residential areas, consequently listing price tend to be related to the properties value in neighbourhoods as well the average rental price in the neighbourhoods. When housing prices are higher, listing prices tend to be higher (Chen and Xie, 2017 ; Kakar et al., 2016). Furthermore, Airbnb listings prices are higher close to the city centre compared to lising prices located further away of the city centre (Gibbs *et al.*, 2018; Wang & Nicolau., 2017). However, main sights are more spread out of cover than only the city center. Few studies focused on the Airbnb listing prices in relation to the key activities of interest for tourist during their city trip, which are visiting main sights (Cai *et al.*, 2019; Lladós-Masllorens *et al.*, 2020). However, both studies only took only into account distance to nearest and neglected potential amenity effects located beyond nearest. Tourists visit cities for a short time period, therefore it is likely they want to locate on places where main sights tend to cluster (Barros & Machado, 2010). Hence, proximity to an attractive touristic area in a low-density area may be overvalued and proximity to an attractive touristic area in a high-density attractive touristic area may be undervalued in these earlier studies. Seresinhe, Moat and Preis (2018) argue the application of user-generated geotagged photos by a photo web sharing site can improve the estimates how people perceive an area compared to models with only basic measurements[1]. In addition, according to Li *et al.* (2018) multiple data sources can

[1] A method to measure perceptions of location quality is the application of big data as big data offers possibilities to investigate phenomena using spatial temporal data. Regarding tourism research, the indirect usage of geolocated big data provides better insight in tourism mobility, tourist demand, tourist consumption and tourists spatial behaviour (Li *et al.*, 2018; Marti *et al.*, 2020). For instance, Paldino *et al.* (2015) used the number

reveal a more comprehensive insight into the tourists system compared to applying one single type of big data such as user-generated geotagged photos. In this context, what is missing is a study towards the capitalization of location quality into Airbnb prices taken into account distance to main sights as well consider areas perceived attractive by tourists. Furthermore, as such, this study aims to gain a better understanding of the amenity value of main sights by focusing on both perceived attractive touristic area by tourists as well distance to the nearest main sight. To obtain a better understanding of the amenity value of attractive touristic areas the following research question will be answered.

To what extent attractive areas are reflected in Airbnb listing prices in the urban environment?

For this study, the main sights of interest for this research will be based on the most popular sights according to TripAdvisor. TripAdvisor ranks using an algorithm main sights according to user review scores. Additionally, this study will make use of Instasights that measures the Geo popularity of places. This popularity is based on "billions of user-generated geotagged signals, regularly indexed across 60+ public sources" and will be used in order to define the most attractive touristic areas (Instasights, 2020). Instasights consist of four heat maps with touristic activities, this study focus on the sightseeing heat map following the line of reasoning of previous studies (Arbel & Pizam, 1977; Paldino *et al*, 2015; Gutierrez *et al*, 2017).

We follow most studies in property valuation in applying hedonic price models to decompose Airbnb prices and to estimate the implicit value of location quality (Wilkinson 1973; Daams *et al,* 2016; Wang & Nicolau, 2017)[2]. The dataset on rents used for this study is sourced from Inside Airbnb provides. Rome is selected as case study since it is one of the most appealing touristic cities in Europe. Around 9 million people visited the capital of Italy in 2019 (Statista, 2020). Besides, the city has many historical amenities that makes it an interesting city to investigate how these amenities are reflected in Airbnb listing prices. In addition, the harmful effects caused by Airbnb such as decreasing liveability and housing affordability mainly apply to large European cities such as Rome. The overnight stays in hotel increased from 22,9 million in 2012 to 30,1 million in 2018 that is an indication of mass tourism in Rome. These tourists stay on average only 2,4 days in the city of Rome (Statista, 2020). Hence, the possible externalities of that make a study of this kind even more pressing. Decreasing housing affordability can also be observed in Rome as prices in the historic inner city have significantly risen

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of user-generated geotagged photos as proxy to determine which areas residents and tourists find most attractive in a city.

[2] Hedonic price models are often used to investigate how utility regarding internal and external attributes of the property are reflected into real estate prices. These models can also be applied to the Airbnb market where listing prices are based on internal and external attributes (Wang & Nicolau, 2017).

in recent years (Savills, 2019). In addition, Airbnb pricing studies in the city of Rome have not been done yet.

In addition, this study considers the variation of the effect between submarkets of Airbnb. A methodological limitation of previous Airbnb pricing studies is that they all rely on pooled estimations samples in investigating prices but given the heterogeneous supply of Airbnb, it is plausible that prices differ across room types. Lutz and Nieuwlands (2018) found out that private rooms and entire houses attract different tourism segments. Hence, it may be that how location quality is reflected in listing prices is differently per submarket based on pricing levels. The following research question will be answered. As such, this study has three contributions. First, it explicit measures the possible distance decay of the capitalization of attractive touristic areas into Airbnb listing prices. Capitalization is measured as listings being in the vicinity of sightseeing areas. Second, this study consists to the growing body of real estate pricing literature that focus on measuring the perception of location quality (Daams, Sijtsma & van der Vlist., 2016) (Sanchez *et al*., 2018) (Paldino *et al.*, 2015). Third, this study measures how the possible distance decay of attractive touristic areas differs per price segmentation in the Airbnb market.

2. Background on Airbnb in the sharing economy

The 21th century is characterized by a trend where individuals more often want to rent and borrow goods rather than to buy and own them. A new economy, the sharing economy, has emerged from the change in behaviour in combination with technological innovations (Belk, 2014). The sharing economy allows individuals to share private assets with other individuals by use of digital platforms (Belk, 2014). A term for the sharing of such goods like Airbnb is collaborative consumption. Belk (2014, p.5) defines collaborative consumption as “people coordinating the acquisition and distribution of a resource for a fee or other compensation”. A wide accepted definition of researchers is the definition of Frenken *et al*. (2015) who defines the sharing economy as “consumers granting each other access to their underutilized psychical assets possibly for money”. The sharing of underutilized goods takes a central stand in the sharing economy. According to Nieuwland & Melik (2018), Airbnb is often used as a profit model where investors and private individuals buy up houses and rent it at a platform as Airbnb. Airbnb is no longer only a platform for a more cost-effective use of assets as argued by Frenken *et al*. (2015). Consequently, Airbnb more adheres to the definition of Belk (2014) than the definition of Frenken *et al*. (2015) keeping in mind that some hosts have multiple houses and want to make profit. In the Airbnb market, hosts have the possibility to implement their own listing prices. In general, hosts have difficulties to determine the real market value for their listing. Although Airbnb provides price tips features for hosts, this tool lacks transparency (Gibbs *et al.*, 2018).

Airbnb describes itself as “a trusted community marketplace for people to list, discover, and book unique accommodations around the world” (Airbnb, 2019). The advantages of Airbnb accommodations for tourists compared to hotel lodgings have caused Airbnb to be a disruptive force in the accommodation sector. Guttentag (2015) states that this are products that do not have traditional attributes, however they offer alternative benefits and can transform and dominate a market in relative a short time period. In general, these disruptive products are perceived as more convenient and cheaper than the old business models such as hotels. Next to the advantages for tourists, Airbnb can also have specific advantages for cities. Airbnb may better distribute the income across less touristic neighbourhoods since Airbnb listings arise in residential areas. This could enhance local economic growth such as an increase in employment in sectors relating to tourism like restaurants and bars which benefit of a mix of tourists and local citizens (Economic Policy Institute, 2019). For instance, Alyakoob and Rahman (2018) found empirical evidence that restaurant employment increases by 3 percent if there is an increase of Airbnb density by 2 percent in a particular neighborhood.

On the other hand, negative spill overs arise in cities having many Airbnb listings. Airbnb causes house- prices and rents to rise in areas with a high density of Airbnb listings. (Sheppard & Udell., 2016; Sugu, 2018). Sheppard & Udell (2016), outline how an attractive location will affect property values. An increase in demand for housing due to an increased popularity for Airbnb will cause rents to increase because there is a fixed supply of housing in the short term. Consequently, house values will increase due to a lower cost of ownership. Furthermore, Zervas, Proserpio & Byers (2017) found that Airbnb has a negative impact on hotel revenues variating between the 8 and 10 percent in a research in Texas. The spill over effects of Airbnb on other real estate markets and on liveability in cities has resulted in city governments putting in place well-considered regulations against Airbnb to reduce these negative effects. Regulating short-term rental in the US mainly focusses on tax payment and liability while European cities mainly focus on quantitative measures such as limiting the number of days a host can rent out his home (Nieuwland & Melik, 2018).

3. Theory on Real Estate Location Pricing

The real estate market differs from other markets as it is reasonably assumed that the real estate market is relatively inefficient and property is heterogeneous (Wilkinson, 1973; Tiwari & White., 2010). Real estate objects vary in building material, age, the number of bedrooms. Consequently, a real estate object is hard to compare and buyers do not have full transparency on the market. Therefore, according to Wilkinson (1973), real estate objects can be seen as a hierarchy consisting of internal (e.g., building characteristics) and external (e.g. location) attributes. Regarding the price of real estate objects, a fundamental assumption is that price of a property reflects the utility of a property to a consumer where consumers, in this study tourists, want to maximize utility for attributes (Wilkinson, 1973; Rosen, 1974). Concerning the internal attributes of properties, three types of Airbnb listings are distinguished in general. These are entire rooms, private rooms and shared rooms. Entire homes are the most selected type of rooms (Lutz & Nieuwland, 2018). It is noticeable that entire rooms given their surface have the most value-added effect, and shared rooms the least value added effect due to lack of privacy and their small size. Likewise, to other real estate markets, tourists seek for a location that maximize their utility, as such location is one of the key attributes that is reflected in the price of Airbnb listings (Wang & Nicolau., 2017).

In understanding how land rents capitalize in property prices, the literature often refers to the bid rent model (Alonso, 1960). The theory compares a lot of living space further away from CBD with good accessibility close to the CBD where the living space is smaller (Alonso, 1960). The theory can also be applied to the hotel industry and other accommodation sectors when there is a trade off between location and a quantity of land and a hierarchy of land use (Egan & Nield, 2000). The most expensive hotels are located closest to the city center as there most amenities are located and outbid budget hotels which are consequently more located at the edges of cities (Egan & Nield, 2000). The presence of amenities in the vicinity results in external price effects that are reflected in property values (Wilkinson, 1973). It is likely that such external price effects are also internalized into Airbnb listing prices.

How amenities result in external price effects can be explained by the amenity based theory of Brueckner, Zenou and Thisse (1999). They state that the location of particular income groups depends on the topology of amenities in a city (Brueckner *et al*., 1999). The higher income groups will settle where the amenities are as the marginal valuation of amenities rises sharply with income (Brueckner *et al*., 1999). Those amenities consist of natural amenities (e.g., lakes), historical amenities (e.g. monuments) and modern amenities (e.g. theaters) (Brueckner *et al*., 1999). European cities have rich histories and therefore many historical amenities can be found in the cities. These historical amenities can be assumed to highly correlate with the main sights. Such main sights obtain their popularity by having historical value, excellent architecture, or the possession of rare nature phenomenon that can be perceived as exogen amenities. In general, the higher income groups want to live in the vicinity of exogenous amenities (historical and natural amenities) and the endogenous amenities tend to follow the rich people (Brueckner *et al*., 1999). Consequently, prices will rise in the surroundings of those exogenous amenities. For instance, Ruijgrok (2006) found out that house prices which are in the surroundings of historical amenities rise with 15 percent in Tiel. Daams *et al*., (2016) found evidence that attractive nature spaces have a positive effect of 16 percent on properties prices within 0,5 kilometer to 1,6 percent for properties located 7 kilometer away from the nearest attractive nature space. In the Airbnb market, Airbnb listings are likely to be associated with main sights and want to locate in the vicinity of such sights as tourists may end to move around the main sights of a city (Gutierrez *et al.*, 2017; Paldino *et al.*, 2015). In the accommodation sector, this implies that prices of Airbnb listings close to exogenous amenities should be higher as opposed to prices of listings further away from exogenous amenities given a higher demand for accommodations.

To what extent the positive effects of amenities are internalized over distance is dependent upon the difference in location quality between the inner city and peripheral areas. First, tourists value location in the surroundings of intersections such as bus stations, main roads in the city and train stations (Birgin, 2000; Aliagaoglu and Ugur, 2008). In general, public transport is the preferred mode of transport for tourists in urban destinations next to walking (Hall *et al.*, 2015). Hence, if cities rely on a good public transport network tourist have an incentive to stay in more peripheral areas driven up prices in these areas and diminish the positive price effects of exogenous amenities. Especially in western countries the public transport network is more developed (Hall *et al.*, 2015). A moderating role here is transports costs as high transports costs may diminish the positive effect of a location of an accommodation close to a main public transport network connection. In central areas accessibility to public transport networks is less of importance as most properties have convenient public transport connections in these areas (Fang *et al*., 2019). Second, the externalities of tourism may play a role in how location quality is reflected in prices. Mass tourism in the city center may be an incentive for tourists to stay in peripheral areas instead of central areas driven up prices in peripheral areas due to higher demand as peripheral offer a quieter environment (Cro & Martins, 2018). Third, when inner cities suffer from economic and psychical decline, tourists have an incentive to stay in peripheral areas where new developed neighbourhoods arise. It is likely that endogenous amenities will arise in these new developed neighbourhoods driven up prices in peripheral areas due to higher demand and decreases prices in central areas (Rogerson, 2014; Cro & Martins, 2018). This implies that the geographic context and urban morphology plays a key role how exogenous amenities are reflected into listings prices.

From another point of view, tourism demand for accommodations differs per consumer segment that may have implications how location quality is reflected into Airbnb listing prices. Peer to peer accommodations, such as Airbnb, is mainly used by leisure travellers. In the Airbnb market, people staying in shared rooms are more often individuals seeking for social interaction while entire homes attract more couples (Lutz & Newlass, 2018). In addition, entire homes are more used by higher income groups while lower income groups use shared rooms more often. This implies that budget constrains play a role in selecting an Airbnb room type (Lutz & Newlass, 2018). However, high-end tourism is gaining more popularity and it is expected that growth will continue at a fast rate (Howarth, 2011). An increasing number of tourists who normally stay in low- and middle end tourism accommodations are staying in high-end tourism accommodations to temporarily take on a different lifestyle (Moscardo & Benckendorff, 2010). A moderating role here is that the increase of low-cost flights to destinations may encourage people to spend more money at the destination, for instance staying in higher priced accommodations, due to saving money with transport (Martin & Sentis, 2016). Another novelty of high-end tourism is that they are seeking for new experiences which could be visiting new destinations but also revisiting previous destinations in an innovative way (Howarth, 2011). A way of getting new experiences is staying in unique accommodations and it is plausible that the Airbnb market offers unique accommodations as Airbnb listings can arise in existing residential areas. Therefore, it can be reasonably assumed that the supply of Airbnb is more heterogonous than other accommodation sectors. According to Gibbs *et al.* (2018) Airbnb listings differs from penthouse apartments to private islands, which offers high-end tourism opportunities to experience destinations in another way. Moreover, high end tourism focuses more on quality of facilities, service and comfort and less on accessibility to desirable locations (Moscardo & Benckendorff, 2010). In the hotel industry, the impact of location on prices diminishes if an accommodation reaches a higher quality level (Yang *et al*., 2016). As such, location to central areas may be less reflected in accommodation prices as the internal attributes of the property, which are in general stronger drivers of price.

Hypotheses

H1*: Close access to amenities is positively reflected into Airbnb listing prices.*
Tourists visit cities for a short period, therefore it is likely that they want to be located near amenities. For tourists, attractive amenities correlate with the main sights in the city as tourists' value accessibility to these type of amenities (Wilkinson, 1973; Bruckner *et al*., 1999; Barros & Machado, 2010; Paldino *et al.*, 2015).

H2*: The possible positive price effects decays with distance*
Rome is an historical city and main sights can mainly be found in the city centre. Therefore is it likely that prices will be highest in the central areas and decays if the distance to the central area increases (Alonso, 1960; Egan & Nield, 2000)

H3*: The relative magnitude of the internalization of the external benefits of amenities into Airbnb listing prices differs between the lower and higher priced market segmentation.*

It can be expected that the lower price segmentation is more sensitive for being located close to exogenous amenities compared to the higher priced segmentation as it is likely that quality factors are stronger drivers for price than accessibility for these higher price Airbnb properties (Moscardo & Benckendorff, 2010; Yang *et al*., 2016). .

4. Methods and data

4.1 Study area

Rome it the capital of Italy and is known as appealing sightseeing destination. In 2012, there were 2,6 million individuals registered in Rome. This amount has been grown gradually to 2,8 individuals registered in 2019 (Statista, 2020). Rome is the eight largest city in Europe in terms of population. The population density corresponds with 2,232 citizens per hectare. In contrast to other major European cities this density in relatively low. In contrast, Berlin has a population density of 3,997 citizens per square kilometer and Madrid has 5,432 citizens per square kilometer. Paris has a population density of 21,435 citizens per square meters (World population review, 2020). That the population density is relatively low is mainly due to the large surface of the city. In terms of surface, the city is larger dan Paris and only slightly smaller than London (Montanari *et al.*, 2010). Concerning land use, most parts of the city are open spaces and public spaces. Residential areas occupy only 18 percent of the total surface while unbuilt area cover 73 percent of the metropolitan area (Montanari *et al.*, 2010). Rome has a rich history and many historical buildings are found in the city. The Tiber river flows through the city and the dissects the southern and northern part of the city. The Roman Forum, the Palatine hill and the Colosseum are the most appealing touristic attractions, visited by over 7.6 million tourists in 2018 (Statista, 2020). The historic centre, which consist of the neighbourhoods Tridente, Corso Vittorio (Parione), and Sant'Angelo- Campitelli has the most appealing touristic attractions. However, several other appealing attractions are more spread out of cover in the city.

4.2 Identifying attractive touristic areas

This study applies multiple indirect big data sources in identifying attractive touristic areas. Big data transfers large information assets into value which requiring specific analytical methods such as algorithms (De Maura, Grimaldi & Greco, 2014). Boyd and Crawford (2012, p8) claim that "Big Data is less about data that is big than it is about a capacity to search, aggregate, and cross reference large data sets". This definition relates to the interplay between technology, Analysis and mythology. This relates to algorithmic accuracy, understanding patterns based on large dataset and the belief that large data sets produce a high form of truth objectivity and accuracy of real-life phenomenon. Consequently, big data provides better insights in how we understand and organize society (De Maura, Grimaldi & Greco, 2014). There is no theoretical guidance to determine the amount of attractive touristic areas should be incorporated in understanding the amenity value of attractive touristic areas. For instance, Lladós-Masllorens *et al.* (2020) incorporated the seven main sights in Barcelona into account in relation to Airbnb listing prices. Cro & Martins (2018) identified 13 main sights in relation to hotel prices in Lisbon. They only selected the most popular as it is likely that less popular main sights does not have an accessibility value for tourists and tourists visit cities for a short time period

(Barros & Machado, 2010). For this study, likewise to the research of Cro & Martins (2018), the main sight of interest are based on TripAdvisor (2020). TripAdvisor ranks main sights using an algorithm that is based on more than 300 million user reviews. The eight most visited sights are taken into account, which are hereafter known as attractive touristic areas. Among these sites are the Pantheon, Colosseum, Roman forum, Piazza Novana, Trevi Fountain, Basilica di Santa Maria Maggiore & Galleria Borghese. Additionally, the most important main sights of Vatican City are also included as the two cities are interrelated and therefore the Airbnb market (Appendix). Consequently, ten attractive touristic areas are taken into account for this study.

The additional measure for measuring how perception of location quality internalize into Airbnb listing prices will be measured using Instasights. Thus far, in scientific research, Samantra-Cruz *et al.* (2017) used Instasights to detect areas in a city with high concentration of users, Sanchez *et al*. (2018) delineated the touristic area by the intersection of the four layers of social relevance on Instasights and Marti *et al*. (2020) was able to detect touristic activity centres using Instasights. Marti *et al*. (2020) validated the use of Instasights as a valuable information source and argued the heatmaps can be used in scientific urban studies. The authors state that specific points of interest can be identified in touristic cities can be identified rather than only popular individual venues. As a means of using big data in scientific research, Instasights has several advantages. First, a large chuck of multiple data sources is cross-referenced. Second. It is a dynamic source as the user perception is constantly updated globally. Third, there is accounted for differences between countries, as sources (e.g., Instagram) are more popular in a particular country compared to another country. Therefore, weights are given to the different sources depending on the geography. In addition, sources are updated frequently which is in line of reasoning with the concerns of Liu *et al*. (2018) who states that a large number of studies rely on outdated sources (e.g. Flickr) instead of more recent and popular sources such as Instagram. Furthermore, another large advantage of Instasights is the spatial precision of the data as touristic activities are projected to the street corner level and touristic activities cover all parts of the world (AVUXI, 2015). User generated perceptions having geo-coordinates are analysed and indexed as the algorithm of AVUXI works similar to that of Google PageRank. The most perceived attractive areas are located in the historic inner city (Appendix A). The data cannot be downloaded. Hence, a screenshot of the sightseeing category layer is imported to ArcGIS. ArcGIS is an analysis, mapping, and data storage system hosted by ESRI (ArcMap, 2019). The georeferencing tool is used to add spatial coordinates to the Instasights layer (Appendix B).

4.3 Airbnb Data

The available dataset for the Airbnb listing characteristics is provided by third-party website Inside Airbnb. Inside Airbnb is a non-commercial party, which scrapes public data from the Airbnb website and is publicly available for promoting scientific debate about the Airbnb market (Cox, 2020).

Inside Airbnb, list all properties that were bookable on a given date. Inside Airbnb provides a comprehensive overview of information about the different listings. The original dataset consists of cross-sectional data with 107 variables. The data is obtained on 28 July 2019. One of the variables is the Airbnb listing price, which is the dependent variable of interest for this study. Additionally, the longitude and latitude of the listings are provided which make it possible to measure the Euclidean distance to the nearest attractive touristic area from an Airbnb listing. A graphical spatial representation makes clear that most expensive listings are in the city centre and the amount of higher priced listings decays over distance (Figure 1).

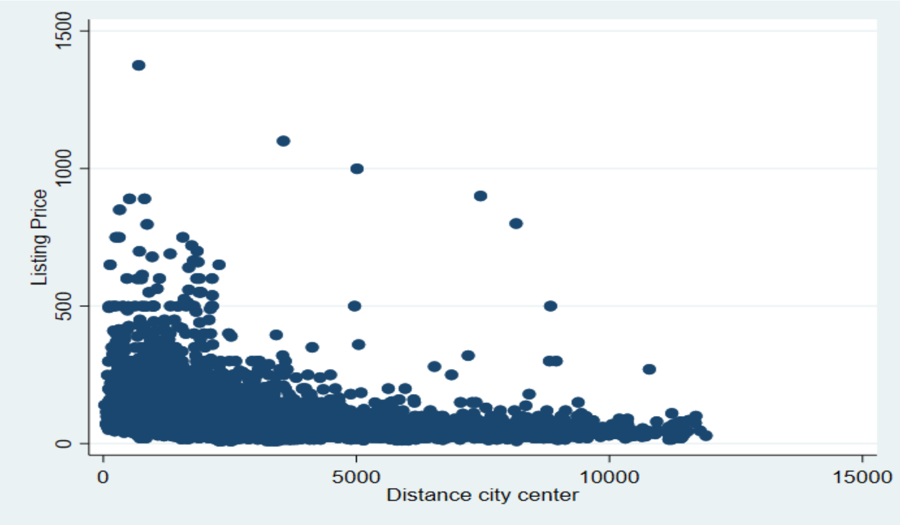

Figure 1*: Relationship listing price and distance to city center (Via del Corso)*

Furthermore, the dataset contains of cross-sectional data. As such, the model will not be able to capture seasonality as well differences that can be accounted to differences in time. Nevertheless, there is accounted for, as Rome is less sensitive for seasonality as Rome is an attractive city throughout the year in comparison with other regions of Italy (Savills, 2019). An important consideration while interpreting the results of this study is that the listing price is whether the listing is bookable on a certain day. The actual reservations are not known. However, there is as much as possible accounted for by only incorporating active listings. In addition, previous wide acknowledged studies used the scraped Airbnb data from Inside Airbnb (Wang & Nicolau, 2017; Gibbs *et al*. 2018)

4.4 Control variable selection

Next to location, other factors have an important role in explaining Airbnb listing prices, may correlate with location, and should therefore be considered as control variables. The variables that relate to the building characteristics of the property are the number of bathrooms, bedrooms, accommodates and room type. Previous research showed that these characteristics have the most impact on Airbnb listing prices (Wang & Nicolau, 2017; Gibbs *et al*. 2018). Yet, in the Airbnb market, some market specific characteristics are reflected in Airbnb listing prices that are not common in other real estate markets. The Airbnb market is operating in a peer-to-peer market and therefore is built upon trust between the host and guests. Thus, review scores of the property and status of the host are important in the Airbnb market (Chen & Xie; 2017). The variable Superhost will be included as the role of the host is important in the Airbnb market (Wang & Nicolau, 2017). If a host is experienced in rent out properties and on average has good reviews, he will get a 'superhost' status. Specifically, this means that a host has had more than 10 guests in a calendar year with at least 80 percent review score rating. Besides, the host responds on messages within 24 hours and does not cancel current bookings (Airbnb, 2019). The variable host listing count is included as professional hosts adopt on average a higher listing price compared to listings of single hosts (Kwok & Xie, 2018).

Important determinants that do not belong to the host or psychical attributes of Airbnb listings can be categorized into advertisement features that contains rental policy and review indicators. Gibbs *et al*. (2018) emphasize that rental policies are important in explaining prices that can be implemented by the host. Inside Airbnb provides multiple review indicators. This study will consider the number of reviews per month because this number is more representative than the total number of reviews as there are substantial differences in the time of the first review. Furthermore, the dataset has many variables focusing on review scores. This study will only consider the total review score. Regarding the rental policy, there are five different values. However super strict 60 and super strict 30 account for only 18 and 35 of the observations respectively. Consequently, these two types are combined with the normal strict policy resulting in flexible, moderate and strict policy.

Furthermore, a listing price of a property may be based on listing prices of properties in the surroundings. Therefore, we include neighbourhood dummies to control for spatial dependence in pricing. In total, 15 neighbourhoods are included. Following a recent study, it is possible that the listing price is dependent upon internal market competition as agglomeration effects arise in areas having many Airbnb listings (Xie *et al*., 2020). Specifically, this relates to the number of Airbnb listings in the same district. A density dummy will be included to test whether prices are significant higher in areas having many Airbnb listings. The dummy relates to zip codes having more than 1,000 listings within a tract (N=2). Property amenities such as the presence of a pool also affects Airbnb listings prices, however previous research showed the effect on Airbnb listing prices is small (Gibbs *et al*., 2018; Wang & Nicolau., 2017). As such, it is plausible that not being able to observe those amenities will not result in omitted variable bias. To summarize, the control variables that are included relate to the building characteristics, host attributes and advertisement features.

4.5 Descriptive statistics

The total sample size is 10,051 individual Airbnb listings[3]. Figure 2 shows the listings that are

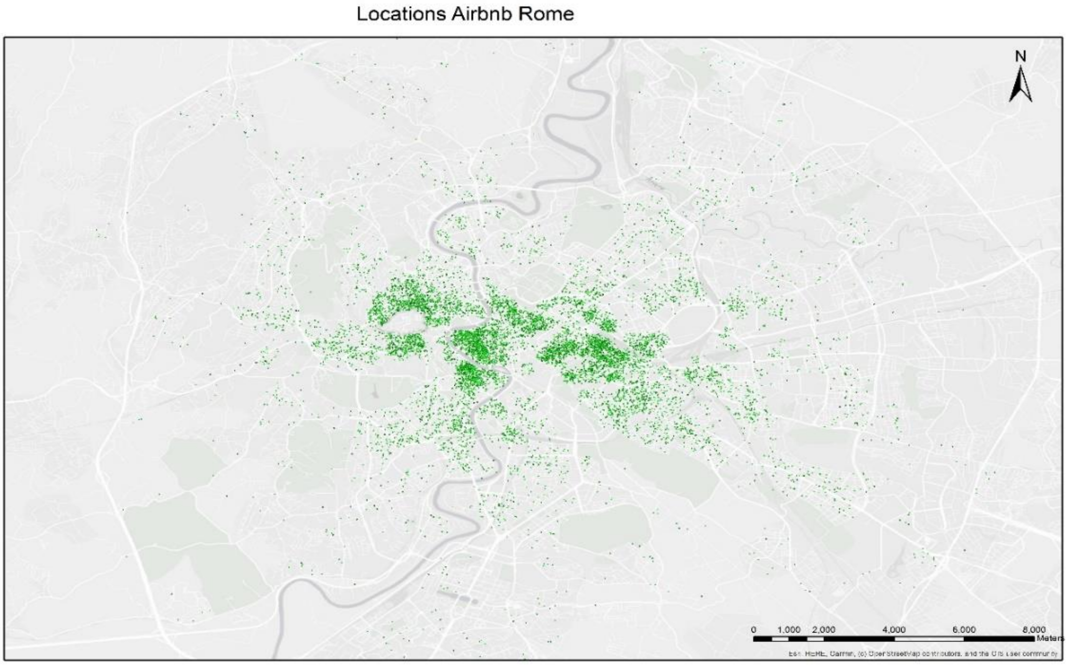

Figure 2: Airbnb listings Rome. Source: Arc map and InsideAirbnb

taken into account for this study. Most listings tend to cluster around Vatican City, the historic inner city and the eastern part of the city. The average per-night price of an Airbnb room in Rome is 88.3 euro on July 28. The average price ranges from 9 euro to 1,375 euro. This study will not remove the outliers, as one of the aims of this study is to get more insight in the lower- and higher priced market segmentation. Table 1 shows the selected variables and the descriptive statistics of this study.

Table 1: *Descriptive Statistics for the Airbnb Sample (N = 10,051)*

Variable	Mean	Std. Dev.	Min	Max
Price per night	89.425	72.206	9	1,375
Bathrooms	1.289	0.663	0	12
Bedrooms	1.432	0.844	0	12
Accommodates	3.815	2.141	1	16

[3] Not all data of Inside Airbnb is seen fit for the empirical analysis. First, to distinguish active vs non-active listings only listings are selected with at least one review a year. According to Ye *et al*. (2009), reviews are a good indicator of demand in the hotel sector. For this paper, it is assumed that reviews in the hotel industry and in the Airbnb market are comparable. Second, listings are removed which are located outside the outer city ring (559 observations). These listings were mainly more than 20 kilometer located outside the city of Rome. As this study is only focusing on the metropolitan area, these listings were removed as it could cause bias coefficients. Additionally, missing information about hosts (26 observations), building characteristics (4 observations) and zipcodes (164) are removed as well.

Room Type	.	.	.	.
(D) Room Type – Entire home/apt	.684	.465	0	1
(D) Room Type – Private room	.305	.46	0	1
(D) Room Type – Shared room	.011	.104	0	1
Rental Policy	.	.	.	.
(D) Rental policy – Flexible	.296	.457	0	1
(D) Rental policy – Moderate	.505	.5	0	1
(D) Rental policy – Strict	.199	.399	0	1
Review scores rating	93.258	7.576	20	100
Reviews per month	1.993	1.741	.03	20
(D) Superhost	1.329	.47	1	2
Host listings count	6.304	15.106	1	326
(D) Nearest TA < 0,25 km	.098	.297	0	1
(D) Nearest TA < 0,5 km	.168	.373	0	1
(D) Nearest TA < 0,75 km	.142	.349	0	1
(D) Nearest TA < 1 km	.123	.329	0	1
(D) Nearest TA < 2 km	.191	.393	0	1
(D) Nearest TA < 3 km	.115	.32	0	1
(D) Nearest TA < 4 km	.073	.26	0	1
(D) Nearest TA < 5 km	.035	.183	0	1
(D) Perceived attractive space	.304	.46	0	1
(D) High density area	.248	.432	0	1

Note: TA stands for touristic area. (D) Are dummy variables.

In Rome, most Airbnb listings are Entire homes (68,15 percent), followed by private rooms (30,71 percent) and shared rooms (1,13 percent). On average, each listing has 1,3 bathrooms, 1,4 bedrooms and can accommodate 3,8 people. Furthermore, 65,9 percent of the hosts has two of more listings. Besides, 32,43 percent of the hosts is a superhost. The average review score is high with a mean of 93 out of 100. Listings in Rome are on average reviewed twice a month. 40,8 percent of the listings are located within 750 meters of the nearest attractive touristic area. The distance intervals between 2 and 5 km from the nearest attractive touristic area only account for 22.3 percent of the total Airbnb listings in Rome. 30,3 percent of the listings are located within perceived attractive space. Specifically, 17,6 percent of the total private rooms is located in this area. On the other hand, 36,5 percent of the total entire homes is located within the delineated perceived attractive area.

4.6 Main empirical methods

Hedonic price models are used to estimate the effect of location quality on Airbnb listing prices. The ordinary least squares (OLS) technique is applied to investigate the main models.

Elaboration on the OLS assumptions is included in the Appendix (C). The Airbnb listing price is the dependent variable of interest and can be explained by location and a set of control variables. For the explanatory variables, the building characteristics (B), host attributes (H), advertisement features (R) and the locational factors (L) are included. This gives the following theoretical hedonic equation.

$$Price = f(B, H, R, L) \tag{0}$$

To estimate this equation empirically, multiple models are specified. First of all, the baseline specification.

$$Ln\ P_i = \beta_0 + \beta_1 (Room\ Type) + \beta_2 (Bathrooms) + \beta_3 (Bedrooms) + \beta_4 (Accommodates) + \beta_5 (Review\ Score) + \beta_6 (Reviews\ per\ month) + \beta_7 (Rental\ Policy) + \beta_8 (Superhost) + \beta_9 (Host\ Listing\ count) + \beta_{10} (Airbnb\ Density) + \beta_{11} (\boldsymbol{Neighborhood}) + \varepsilon_i \tag{1}$$

Where *Ln (P_i)* is the natural logarithm of the listing price of property i. The dependent variable is transformed to a log variable as the listing price data has a right-side tail. Due to the presence of heteroscedasticity, robust standard errors are used in the first and third model. Clustered standard errors in the second model. β_0 is the intercept and the betas (β) are the coefficients to be estimated for the internal and external Airbnb listing attributes. Neighborhood is a vector of fifteen neighborhood dummies. Finally, ε_i is the standard error that is included in all models.

Second, to estimate the impact of location on the Airbnb listing price, model (2) includes the distance from the Airbnb listing to the nearest attractive touristic area and whether the property is located within perceived attractive space.

$$Ln\ P_i = \beta_0 + \beta_1 (Room\ Type) + \beta_2 (Bathrooms) + \beta_3 (Bedrooms) + \beta_4 (Accommodates) + \beta_5 (Review\ Score) + \beta_6 (Reviews\ per\ month) + \beta_7 (Rental\ Policy) + \beta_8 (Superhost) + \beta_9 (Host\ Listing\ count) + \beta_{10} (Neighborhood) + \beta_{11} \textstyle\sum_{d=1}^{d} \mathbf{Dist}\mathrm{TA}_{id} + \beta_{12} (\mathbf{PA\ Space}) + \varepsilon_i \tag{2}$$

Third, it may be that including neighbourhood dummies may absorb variance, which is the result of being located in the vicinity of attractive touristic areas (Daams, 2019). Therefore, model (3) is estimated without spatial controls.

$$Ln\ P_i = \beta_0 + \beta_1 (Room\ Type) + \beta_2 (Bathrooms) + \beta_3 (Bedrooms) + \beta_4 (Accommodates) + \beta_5 (Review\ Score) + \beta_6 (Reviews\ per\ month) + \beta_7 (Rental\ Policy) + \beta_8 (Superhost) + \beta_9 (Host\ Listing\ count) + + \beta_{11} \textstyle\sum_{d=1}^{d} \mathbf{Dist}\mathrm{TA}_{id} + \beta_{12} (\mathbf{PA\ Space}) + \varepsilon_i \tag{3}$$

where **Dist** TA_{id} is a vector of dummy variables indicating whether the Euclidean distance between listing i and the nearest attractive touristic area falls within interval d (0–25 km; 0,25–0,50 km; 0,5–0,75 m; 0,75–1 km; 1-2 km; 2-3 km; 3-4 km; 4-5km). The reference category is more than 5 kilometer located from the nearest attractive touristic area. These intervals are chosen based on the assumption that tourists want to locate on places, which are walkable from the main sights (Arbel & Pizam, 1977; Gutierrez *et al.*, 2017). The intervals allow testing for the distance decay of the external price effect of amenities. It is expected that model (2) will result in positive coefficients between the distance intervals and distance to nearest attractive touristic area as opposed to the reference category. It is likely that the magnitude of the coeffients will differ between the distance intervals. Furthermore, it is expected that listings located in a perceived attractive area (**PA space**) have higher prices compared to listings located outside perceived attractive areas.

5. Empirical results

5.1 Main model with spatial controls

The results for the main models can be found in table 2[4]. The results of the sub samples are provided in the Appendix, which include private rooms and entire homes. The baseline specification (1) shows the impact of building characteristics, host attributes and advertisement features on Airbnb listing prices. The R squared of this model has a value of 58,9 which means that the model explains 58,9 percent in the variance of the Airbnb listing price. As expected, all building characteristics coefficients are significant and positively effect Airbnb listings prices. However, looking at the sub samples within the Airbnb market, the number of bathrooms has a negative effect on private rooms. This implies that each additional increase in bathroom, price decreases with 13,2 percent for this type of listing. Regarding the host attributes, a superhost causes for 7,2 percent higher listing prices compared to listings without a superhost. The role of the superhost is more important in private rooms compared to entire rooms given a higher price premium in this segment. Each host having one more listing decrease Airbnb listings prices with 0.01 percent that implies that professional hosts do not cause for price increases in the Roman market. There are many professional hosts operating in the Roman Airbnb market, which fierce competition and this may result in lower prices (Kwok & Xie; Cai *et al*, 2019). Regarding the review indicators, each one more review per month will cause prices to fall with 4,4 percent which indicates that lower quality listings are more booked in the Roman market

[4] Concerning the f test, all models show a better fit compared to a model without independent variables. Additionally, multicollinearity can often cause problems in hedonic regression. A method for detecting such multicollinearity is the variance inflation factor (Chen & Rotschield, 2010). The result shows that there are concerns of multicollinearity in model (2) as some location variables have values between 5 and 10, however the values don't exceed the critical value of 10 (Appendix D).

which is in line with previous Airbnb pricing studies (Wang & Nicolau, 2017; Gibbs *et al.*, 2018). This negative effect is larger for private rooms compared to entire homes. Additionally, one point increase in review score results in 0,47 percent higher prices.

Model (2) incorporates the effect of distance to the nearest attractive touristic area from an Airbnb listing and the effect of perceived attractive space. The R squared increases to 61,7 percent. The coeffients within 5 kilometer are positive significant on the 5 percent level, which implies that attractive touristic areas are reflected in listing prices. There is a gradual decay in the magnitude of the coefficients within 2 kilometer of the nearest attractive touristic area. The results show that, as opposed to an Airbnb listing is more than 5 kilometer from the nearest attractive touristic area located, Airbnb's within 0,25 km of a attractive touristic area are associated with 66,6 percent higher listing prices, Airbnb's between 0,25 and 0,5 km are associated with 60,6 percent higher listing prices. The two intervals, 1 - 2 and 2 - 3 km, have respectively 39,1 and 23,4 percent higher prices compared to listings more than 5 kilometers away from the nearest attractive touristic area. The positive effect of location on listings within 3 - 4 meter is 9,8 percent compared to listings more than 5 kilometer from the attractive touristic area and decreases to 7,1 percent for listings located within 4 and 5 kilometer of the nearest attractive touristic area. Model (2) also evaluates whether listings located within a perceived attractive space have higher listing prices. The result shows that a property will have a 14,9 percent higher listing price compared to a listing located outside perceived attractive space. Attractive touristic areas are more reflected in entire rooms compared to private rooms. Regarding entire rooms, the distance intervals are significant over all intervals. On the other hand, between 4 and 5 km the location coeffient of private rooms is insignificant. This implies that distance has a negligible impact on listings between four and five kilometer of the nearest attractive touristic area compared to listings more than 5 kilometer from the attractive touristic area.

5.2 Main model without spatial controls

Model (3) shows that the location coeffients for intervals within 2 km has increased compared to the estimates found in model (2) due to excluding the neighborhood dummies. Neighbourhood dummies may absorb variance, which is the result of being located in the vicinity of attractive touristic areas (Daams, 2019). Interestingly, attractive touristic areas are to a lower extent reflected inproperty prices compared to model (2). In addition, properties located within perceived attractive space have a value added effect of 17,6 percent compared to properties which are located outside perceived attractive space which is larger than the results obtained in model (2).

Table 2: *OLS estimations*

	(1) Log listing price	(2) Log listing price	(3) Log listing price

Bathrooms	0.106***	0.102***	0.103***
	(0.0115)	(0.0110)	(0.0111)
Bedrooms	0.0736***	0.0785***	0.0798***
	(0.00892)	(0.00856)	(0.00867)
Accommodates	0.0696***	0.0688***	0.0678***
	(0.00396)	(0.00377)	(0.00383)
Room Type = Private room	-0.331***	-0.305***	-0.311***
	(0.0112)	(0.0108)	(0.0109)
Room Type = Shared room	-1.133***	-1.094***	-1.101***
	(0.0495)	(0.0516)	(0.0512)
Rental Policy = Moderate	0.0414***	0.0357***	0.0353***
	(0.00891)	(0.00856)	(0.00867)
Rental Policy = Strict	0.0317***	0.0154	0.0179
	(0.0118)	(0.0113)	(0.0115)
Review scores	0.00489***	0.00513***	0.00499***
	(0.000650)	(0.000642)	(0.000641)
Reviews per month	-0.0460***	-0.0494***	-0.0505***
	(0.00232)	(0.00233)	(0.00234)
(D) Superhost	0.0692***	0.0688***	0.0701***
	(0.00892)	(0.00856)	(0.00867)
Host listings count	-0.000169	-0.000682**	-0.000614**
	(0.0003)	(0.000298)	(0.000296)
Nearest TA < 0,25 km		0.511***	0.605***
		(0.0318)	(0.0247)
Nearest TA < 0,5 km		0.474***	0.563***
		(0.0297)	(0.0222)
Nearest TA < 0,75 km		0.458***	0.553***
		(0.0292)	(0.0214)
Nearest TA < 1 km		0.372***	0.474***
		(0.0290)	(0.0215)
Nearest TA < 2 km		0.330***	0.384***
		(0.0257)	(0.0201)
Nearest TA < 3 km		0.210***	0.210***
		(0.0229)	(0.0205)
Nearest TA < 4 km		0.0933***	0.0859***
		(0.0233)	(0.0219)
Nearest TA < 5 km		0.0682**	0.0487*
		(0.0271)	(0.0260)
Perceived attractive space		0.137***	0.170***
		(0.0116)	(0.0113)
Constant	3.615***	3.088***	2.974***
	(0.0593)	(0.0645)	(0.0614)
High density area	.0408201***	-0.0198*	No
	(0.0106)	(0.0107)	
Neighborhood dummies	Yes	Yes	No
Observations	10,051	10,051	10,051
R-squared	0.587	0.617	0.606

Notes: TA stands for touristic area. (D) Are dummy variables. The reference categories consist of distance > 5km to nearest attractive touristic area; strict rental policy and shared room. Standard errors in parentheses.

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

5.3 Differences in Price segmentations

Some authors claim that OLS limits the understanding of the real market (Hung, Shang, and Wang, 2010; Wang & Nicolau, 2017). They showed that very few determinants act the same along the whole price distribution and so the capacity of OLS is reduced. In the hotel industry Hung, Shang, and Wang (2010) justify the use of quantile regression in contrast to OLS due to a better explanation of the price determinants in Taiwan. For instance, the age of the building only affects high priced segmentation hotels while it has no effect on the low-priced segmentation hotels. The OLS model did not provide these insights. Quantile regression provides the possibility to investigate the relationship between all parts of the distribution of the dependent variable with predictor variables. Therefore, linear quantile regression is applied to go further than the analysis of the conditional mean of the dependent variable and provide insight in the lower and higher tail behaviour of the distribution of the dependent variable to investigate in the impact of location between the lower- and higher priced market segmentation. Quantile regression can, when pricing may differ between segments as in the accommodation sector, have several advantages over OLS. Quantile regression estimators can be more efficient when the error term is non-normal and is not sensitive for outliers (Buchinsky, 1998; Hung *et al*., 2010).[5]

In the baseline situation, quantile regression shows the median regression line. This is a solution to an optimization problem where the median is a value depending on the sum of the absolute residuals. In the median regression line, half of the data is above the line and the other half is beneath the line. The other quantiles can be obtained in a similar approach as the median by finding a solution to a minimization problem (Koenker & Basset, 1978). This minimization problem is a sum of asymmetrically weighted absolute errors where the corresponding weights depend on the selected quantile. The solution to the minimization problem results in a portion of the data above the line (θ) and a portion of the data beneath the line (1- θ). For the intuition behind the minimization problem, see the paper of Koenker & Basset (1978). A quantile regression quantile can take a value between 0 and 1. This study will focus on the quantiles, $0{,}1^{th}$ $0{,}3^{th}$ $0{,}5^{th}$ $0{,}7^{th}$ $0{,}9^{th}$. Specifying multiple quantile regression lines makes it possible to detect price patterns in the Airbnb market for different price segments. The basic formula for quantile regression can be expressed as

$$Y_{i=} X_i\beta\theta + U\theta_i \tag{3}$$

Where Y_i is the dependent variable that is the Airbnb listings price. X is a vector of regressors, which are the Airbnb listings characteristics and location attributes in this study. U_i is a vector of residuals.

[5] The assumptions of non-linearity and heteroscedasticity adhere to OLS. However, quantile regression make no assumptions about the distribution of the residuals (Koenker & Basset, 1978)

The parameter β has to be estimated. Quantile (Y_i) is the conditional quantile of Y given X. In the baseline situation, quantile regression shows the median regression line, which is the $0{,}5^{th}$ quantile. In this empirical extension, we investigate the impact of the main specification, model (2), in relation to different price segmentations. Models (7), (8), (9), (10) and (11) reveal the results of the quantile regression estimations that can be found in table 3.

The multiple control variables show interesting patterns and are noteworthy as research towards Airbnb is still in its infancy. The results are revealed for the sample of the total Airbnb market. Regarding the building characteristics, bathrooms and bedrooms have unstable coefficients. The impact of bedrooms on price gradually increases from the 0.1^{th} quantile until the 0.9^{th} quantile. In terms of the number of bathrooms, there is a sharp increase in the price capitalization from the 0.1^{th} quantile until the 0.9^{th} quantile[6]. The number of accommodates shows similar price patterns between the lower and higher quantiles. This implies that the capitalization of the number of accommodates in prices do not differ between the lower- and higher priced segmentation in the Airbnb market. Regarding the variables related to the host attributes, the variable superhost is significant over all quantiles with a decreasing capitalization in the highest quantiles. This implies that the role of the host is more important for the lower priced segmentation. This seems reasonable, as there is more interaction between the host and the guests in shared and private rooms compared to entire homes. Interestingly, the impact of host listing count on price is negative for the $0{,}1^{th}$ quantile and positive for the $0{,}9^{th}$ quantile. Moreover, the impact is only significant for the lowest quantile indicating that professional hosts cause for price decreases in the lowest price market segmentation. The capitalization of reviews scores into listing prices shows a small decline in the highest quantile. The number of reviews per month has an increasing larger negative impact on higher priced listings.

Subsequently, the impact of the nearest attractive touristic area on Airbnb listing prices for different market segmentations is addressed. The quantiles of all distance intervals within 3 km have positive significant coeffients as opposed to the reference category more than 5 kilometre from the nearest attractive touristic area. This implies that location has a value-added effect on listing prices for all Airbnb market segmentations within 3 km of the attractive touristic area. Within 3 km of the attractive touristic area the capitalization into listing prices is most pronounce at the lower quantiles and the magnitude of the effect gradually decays to the $0{,}7^{th}$ quantile. The highest quantile shows a sharp decrease in the effect of location on listing prices compared to quantile 0,7. In addition, location does not have a significant impact on the highest quantile after 3 km. This implies that location has a negligible impact on the highest priced market segmentation. Between 3 and 4 km from the attractive

[5] The highest demand segments better evaluate them and are willing to pay for such characteristics. To translate late this to the private sector, buildings characterises can hardly be changed. Hence, the results have important investment implications for homeowners evaluating the purchase of a new house as well large investors focusing on investments in tourism properties.

touristic area a positive significant effect exists for the quantities 0,1 until 0,7. There is a gradual decrease in the magnitude of the positive effect. Likewise, to the highest quantile, location is not significant in the interval 4-5 km for the 0,7th quantile. The quantile regression estimations showed that the lower quantiles are sensitive for location in this interval. This means that location quality is still reflected in listing prices in the lower priced market segmentation and therefore to a further extent than higher priced market segmentation listings. In contrary to previous results, the quantile regression estimations shows that the highest quantile is most sensitive to location regarding listings located in perceived attractive touristic space. The magnitude of the positive effect decays from the highest to the lowest quantile.

Table 3: *Quantile regression estimations*[7][8]

	(1) q10	(2) q30	(3) q50	(4) q70	(5) q90
Bathrooms	0.0361**	0.0992***	0.120***	0.149***	0.198***
	(0.0166)	(0.00954)	(0.00981)	(0.00983)	(0.0233)
Bedrooms	0.0418***	0.0672***	0.0610***	0.0789***	0.0892***
	(0.0121)	(0.00862)	(0.00899)	(0.00997)	(0.0163)
Accommodates	0.0704***	0.0654***	0.0751***	0.0697***	0.0686***
	(0.00494)	(0.00365)	(0.00387)	(0.00389)	(0.00545)
Room Type = Private room	-0.408***	-0.369***	-0.304***	-0.268***	-0.217***
	(0.0169)	(0.0107)	(0.0103)	(0.0148)	(0.0197)
Room Type = Shared room	-1.284***	-1.202***	-1.142***	-1.143***	-0.703***
	(0.0791)	(0.0449)	(0.0460)	(0.0447)	(0.184)
Rental Policy = Moderate	0.0354**	0.0344***	0.0351***	0.0184*	0.0369**
	(0.0149)	(0.0105)	(0.0116)	(0.0101)	(0.0152)
Rental Policy = Strict	-0.00368	0.0104	0.0207	0.0233*	0.0198
	(0.0152)	(0.0148)	(0.0157)	(0.0129)	(0.0172)
Review scores rating	0.00571***	0.00536***	0.00647***	0.00620***	0.00408***
	(0.000994)	(0.000723)	(0.000658)	(0.000746)	(0.00137)
Reviews per month	-0.0355***	-0.0421***	-0.0440***	-0.0493***	-0.0511***
	(0.00461)	(0.00402)	(0.00281)	(0.00268)	(0.00340)
Superhost	0.0595***	0.0700***	0.0408***	0.0585***	0.0551***
	(0.0103)	(0.0115)	(0.00801)	(0.00961)	(0.0156)
Host listings count	-0.00293***	-0.000556	0.000154	8.61e-05	0.000902
	(0.000410)	(0.000598)	(0.000305)	(0.000410)	(0.000661)
Nearest TA < 0,25 km	0.591***	0.647***	0.597***	0.585***	0.551***

[7] Bootstrapping quantile regression is applied to due to the concerns that the outliers have a effect on the sampling distribution which estimate the beta coefficients. By bootstrapping the coefficients, standard errors and t statistics can be obtained. Bootstrapping estimate samples from the total population. In particular, bootstrapping is useful for quantile regression (Koenker & Basset, 1978)

[8] This pseudo R2 measures the goodness of fit by comparing a model with only a intercept and the sum of weighted deviations of the model of interest (Koenker & Machado, 1999). A pseudo R2 takes a value between 0 and 1 where a value close to 1 is perceived as perfect fit. There is not a universal good pseudo R squared value but approximately pseudo R squared having values of 0,20 or more are appropriate (Koenker & Machado, 1999).

	(0.0445)	(0.0304)	(0.0374)	(0.0313)	(0.0684)
Nearest TA < 0,5 km	0.566***	0.578***	0.528***	0.506***	0.473***
	(0.0443)	(0.0285)	(0.0313)	(0.0291)	(0.0707)
Nearest TA < 0,75 km	0.504***	0.540***	0.479***	0.452***	0.392***
	(0.0434)	(0.0257)	(0.0253)	(0.0241)	(0.0631)
Nearest TA < 1 km	0.434***	0.447***	0.385***	0.371***	0.275***
	(0.0385)	(0.0297)	(0.0298)	(0.0277)	(0.0707)
Nearest TA < 2 km	0.369***	0.377***	0.345***	0.301***	0.236***
	(0.0334)	(0.0288)	(0.0260)	(0.0266)	(0.0604)
Nearest TA < 3 km	0.269***	0.245***	0.229***	0.191***	0.119**
	(0.0375)	(0.0236)	(0.0239)	(0.0246)	(0.0513)
Nearest TA < 4 km	0.149***	0.130***	0.0945***	0.0665***	0.0245
	(0.0414)	(0.0195)	(0.0236)	(0.0249)	(0.0667)
Nearest TA < 5 km	0.117***	0.0923***	0.0756**	0.0377	0.0381
	(0.0448)	(0.0281)	(0.0342)	(0.0435)	(0.0672)
High density Area	-0.0187	-0.00417	-0.0159*	-0.00529	-0.0115
	(0.0215)	(0.0146)	(0.00967)	(0.0123)	(0.0139)
Constant	2.732***	2.878***	2.981***	3.175***	3.637***
	(0.109)	(0.0816)	(0.0799)	(0.0800)	(0.180)
Neighborhood dummies	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0,4	0,39	0,39	0,39	0,4
Observations	10,051	10,051	10,051	10,051	10,051

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Critical readers may notice that the difference between the price segmentations mainly occur due to differences between room types as entire homes are on average more expensive than private rooms and shared rooms. However, a quantile regression estimation of entire rooms shows that the highest quantile is less sensitive to location compared to the other quantiles. Furthermore, likewise the main quantile regression specification the highest priced segmentation is not sensitive for location after 3 km (Appendix). On the other hand, the capitalization of location into prices for the quantile 0,1th until 0,7th is approximately more similar compared to the main quantile regression estimation model

6. Discussion

This study adds to the growing number of scientific researches conducted about the perceptions of location quality in relation to real estate pricing. From the results of model (2) it can be seen all distance intervals within 5 kilometer have positive significant coefficients. This implies that prices of properties are higher within 5 kilometre of an attractive touristic area as opposed to properties more than 5 kilometre from the nearest attractive touristic area. The positive effect is largest for properties closest to the attractive touristic areas and the positive effect decays for properties located further away from the attractive touristic area. The coefficients are higher than the linear effect of 3,4 percent captured by Cai *et al*. (2019) in Hong Kong from the nearest touristic attraction. A plausible explanation relates to the urban morphology of the city as Rome has an historical attractive central area resulting in a monocentric price structure whereas Hong Kong is a modern city with lack of historical sights. An additional explanation relates to the type of traveller. Rome is mainly attracting leisure sightseeing travellers whereas Hong Kong is attracting predominantly business travellers (Lei Fang *et al*., 2019). Following the results, it is plausible that tourists prefer Airbnb listings in high amenity parts of the city instead of properties in more peripheral areas of the city as they visit the city for a short period which is in line with previous hotel- and Airbnb pricing studies (Hung *et al*., 2010; Chen & Rotschield, 2010; Gibbs *et al.*, 2018; Wang & Nicolau, 2017). Positive external effects of amenities exist which are reflected in prices due to higher demand to accommodations in the vicinity of these attractive touristic areas.

Entire homes have a higher price premium if these are located within perceived attractive touristic space compared to private rooms. A plausible explanation is that many entire homes are located in the central areas of the city while private rooms are more dispersed throughout the city, which relates to the hierarchy structure of the interurban theory as outlined by Egan and Nield (2000). This theory indicates that accommodation seek for a location that maximise profit and consequently higher quality accommodations outbid lower quality accommodations for attractive locations. As entire rooms are on average more expensive than private rooms these types of room will be more located in the attractive central areas.

To examine the results of main specification further, model (3) is estimated without spatial controls. Consequently, the location coeffients are higher compared to model (2). It is plausible that the attractive touristic location coefficients are overestimated in this model as other locational factors such as accessibility to public transport connections and travel time are more of importance in peripheral areas.

From the quantile regression estimations, we obtain a more in depth understanding of how low and high end tourism demand attach different values to location quality. It can be observed that location quality is most reflected in the lower priced market segmentation implying that low end tourism attaches more value to external attributes such as accessibility to central areas in the Airbnb market. In addition, location quality has a negligible effect on Airbnb listing prices after 3 kilometer of the nearest attractive touristic area regarding the highest priced market segmentation. It might be that high-end tourism prefer less proximity to central areas and focus more on quality factors of the property and quietness of the environment. An additional explanation could be that listings in more peripheral areas of the city are booked for a longer period. Urban tourists, who stay for a longer period, explore more peripheral regions and have more time to visit main sights, which could results in tourists have a lower incentive to stay in central areas (Barros & Machado, 2010). This needs further research for the Airbnb market. Our results, however, give support to the claim of Yang *et al.* (2016)

that the impact of location diminishes if an accommodation reaches a higher quality level in the accommodation sector, at least in the more peripheral areas.

On the other hand, higher priced listings are more sensitive for being located within perceived attractive touristic space. This perceived attractive touristic space is mainly covering the historic city centre and it is plausible that some high-priced unique Airbnb listings are located in the historic city centre which gaining interest from high-end tourism. This result give support to the study of Wang & Nicolau (2017) who found out location has a larger effect on the higher priced market segmentation in the Airbnb market. These results show that the impact of location might differ between central and peripheral areas. Insight in the impact of location on the different market segmentations enables property investors to improve their well-educated investment decisions as low- and high-end tourism demand attach different values to location quality.

This study also sheds a light on some important findings on the Roman market that may be of aid for policy makers. It has become clear that a large number of listings is located within a kilometer of a touristic area: this area account for 51,4% percent of the observations while covering only 4,8 percent of the total study area[9]. These results support previous research of a strong spatial association between the main sights and Airbnb listings in Barcelona (Gutierrez *et al*., 2017). This gives an indication to policy makers that pressure on the housing market exist close to the touristic areas that mainly cover the central parts of Rome. More succinct, this has important consequences and implications for the housing market as the stream of rental income rises and there is an increasing demand for residential space. Generally, if the stream of rental income rises, the cost of owning a home will decrease resulting in higher property values (Sheppard and Udell, 2016). This will result in decreasing housing affordability in the end. This potential effect is smaller for the lowest market segmentation as this study points out that multi hosts cause for a value decreasing effect in this segmentation. Additionally, because of a large number of Airbnb listings being located close to these touristic areas there is an increasing number of tourists in a small vicinity. Rome is already a popular touristic destination, the presence of Airbnb can strengthen overtourism in central areas having many popular Airbnb listings, which relate to the concerns stated by Nieuwland & Melik (2018) about the arguably harmful effects of Airbnb from a policy perspective. In contrast, hotels are more dispersed throughout the city (Gutierrez *et al*., 2017).

As for future research, it may be considered that in the residential market, to which Airbnb is closely linked in terms of location, views are a strong driver of price in property valuations. For instance, a view on an ocean may increase house prices up to 60 percent (Benson *et al*., 1998). Zooming to the neighbourhood level, views on attractive buildings with appealing aesthetic structures may increase property values with 37 percent compared to properties with views on only average

[9] Calculated by using buffer geometry (ArcMap,2020)

quality structures (Bourassa, Hoesli and Sun, 2004). In relating to the historical Roman market, a view on the historical buildings from the Airbnb property may be an explanation for the large price premiums for listings close to touristic areas. Therefore, the location coefficients may be biased, and the impact of location quality might be overestimated. Future research could focus on investigating the association between Airbnb listings and views on historical amenities and the urban environment as the role of views in relating to Airbnb prices has not been investigated yet. Additionally, a recent research of Yang *et al*. (2019) regarding the drivers of Airbnb supply showed that Airbnb supply and the hotel industry supply affects each other simultaneously and not solely Airbnb to the hotel industry. This could have led to omitted variable bias and therefore the location coefficients could be biased. Hence, an avenue for future research towards Airbnb pricing could be focusing on external competitors such as the supply of hotels or the number of other short-term rental operators in the vicinity of an Airbnb listing. In the same vein of this study, future studies can investigate whether the impact of those competitors on Airbnb listing prices varies between the low and high priced market segmentation. Due to time and data limitations, this study was not able to incorporate variables beyond the used dataset.

We acknowledge that the used proxy for amenity value has some limitations that may be addressed in future studies. First, potential amenity effects of attractive touristic areas, which are not taken into account for this research, are neglected as this study only focus on the most attractive sightseeing areas in Rome. Second, although Marti *et al*. (2020) validated the usage of Instasights in urban studies it is not clear how the different levels of centroids are built up. Furthermore density of amenities such as cafés and restaurants around listings is not considered which could have led to omitted variable bias and might have overvalued the effect of attractive touristic areas on Airbnb listing prices. Another consideration regarding the main specification lies in the fact the intervals closest to the attractive touristic areas shows signs of collinearity, although they do not exceed the critical value of 10. As Airbnb, listings tend to cluster in central areas it may wise to rely on other types of regression, such as global weighted regression, in future studies to obtain better insights in the spatial variation of the impact of location. In addition, this study only considered one city, the capitalization of location quality in cities with another geography and less historical amenities can be considered in future studies. Nonetheless, this study may lay a basis for comparing future cross-city comparison on the capitalization of exogenous amenities in the urban environment into Airbnb prices in a consistent way.

7. Conclusions

This study has focused on the amenity value of attractive touristic areas on Airbnb listings prices in the urban environment. The results are based on hedonic price models using ordinary least squares and quantile regression. A proxy for the perceived attractive touristic area is generated from data on popular sightseeing places from Instasights and the attractive touristic areas are based on the most popular main sights according to TripAdvisor. The aim of the research is to get a better understanding of the amenity value of attractive touristic areas in relation to Airbnb listing prices. The results show that location has a large impact on Airbnb listing prices. Tourists are willing to pay a high premium to locate in the vicinity of attractive touristic areas as amenities are reflected in listing prices in the Roman Airbnb market over a distance of five kilometer extensively. The capitalization of location on listing prices gradual decays as the distance to the nearest attractive touristic area increases. A property has an additional price premium if it is located in a perceived attractive area that is mainly covering the historic center. Additionally, the impact of location differs per market segmentation. More succinct, attractive touristic area are to a larger distance reflected in lower priced market segmentation listings compared to higher priced segmentation listings. In addition, the positive effects are more pronounced in the lower priced segmentations. However, in attractive central areas the effect of location is more pronounced in the higher market segmentation. The results of this study are of aid for policy makers to understand the spatial nature of the Airbnb market as well assisting tourism property investors with making well-informed investment decisions.

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Appendix A: Attractive touristic areas

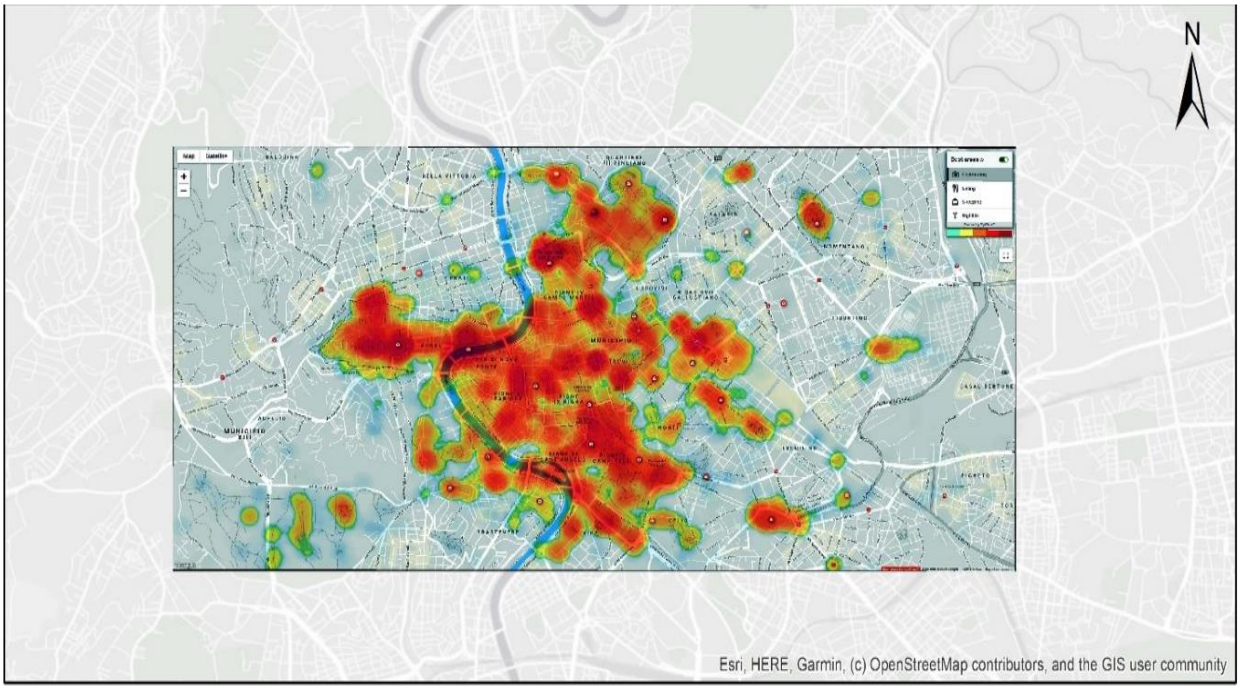


Figure 3. Source: ArcMap & Instasights. If the color becomes more dark it implies a larger concentration of venues with high venues scores for the selected category (AVUXI, 2020)

Figure 4. Selected attractive touristic areas. Source; ArcGis online & TripAdvisor

Appendix B: City Centre

Historic city centre & Main shopping street

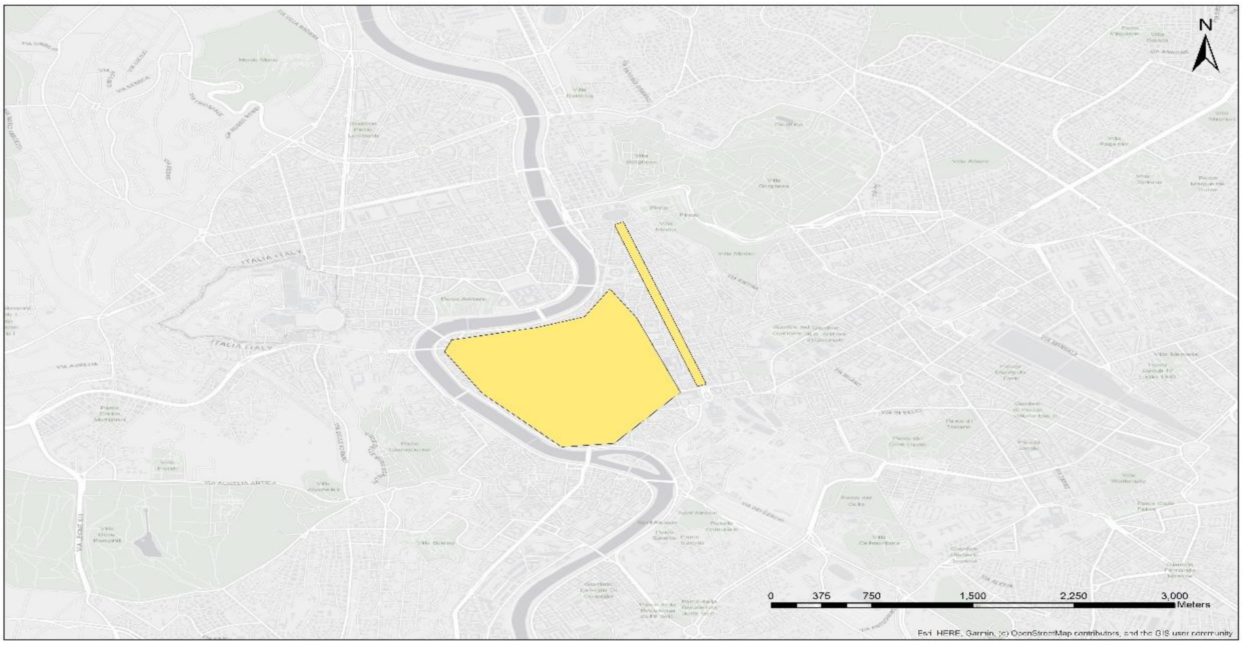
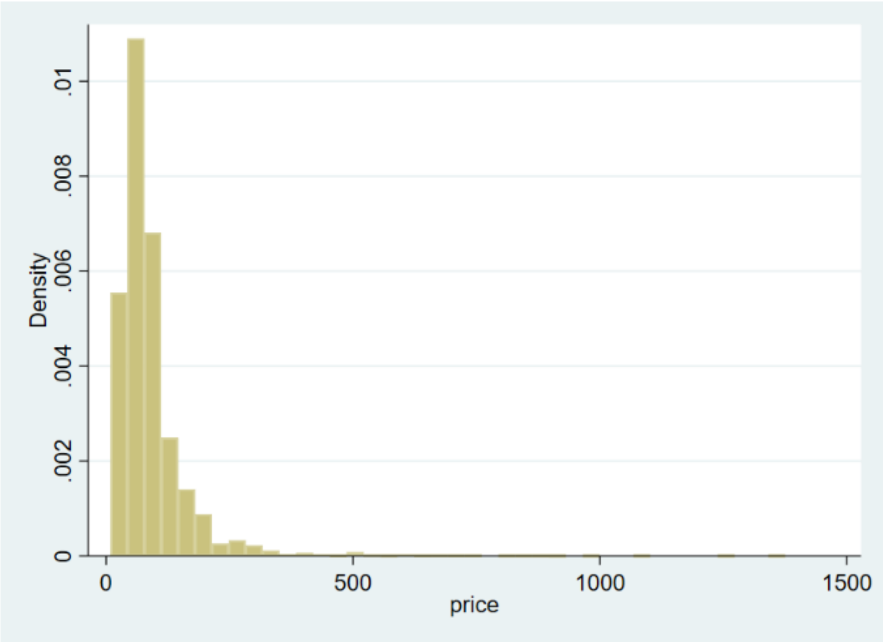
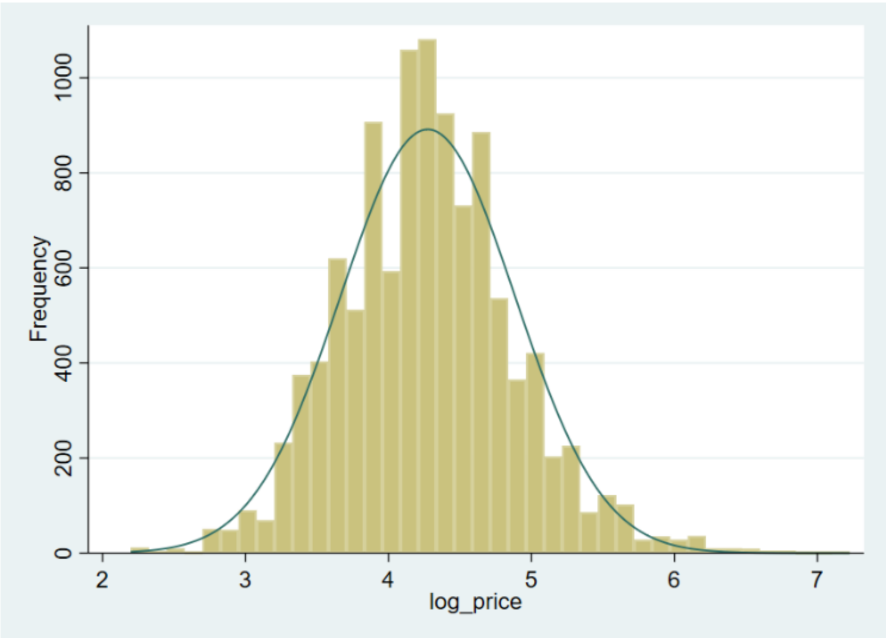


Figure 5 The historic city center of Rome. The Via del Corso, which is the main shopping street, dissects the centre of the historic city centre (Hoteldesartistes, 2020).

Appendix C: Transforming dependent variable



Price



Log price

Appendix D: OLS assumptions

According to Brooks & Tsolacos (2010) the following assumptions are required to use OLS estimations method. When assumptions 1 to 4 hold the coefficients obtained by OLS are blue. This implies that they are consistent, unbiased and efficient, meaning they approximately equal their true value (Brooks and Tsolacos, 2010).

From testing the OLS assumptions, it become clear that heteroscedasticity is present. The variance of the error was not constant. Hence, robust standard errors are used in all four OLS models. The other assumptions were met. A concise description of the different assumptions is given below.

Assumption 1: Linearity $E(\varepsilon t) = 0$

First, this assumption will not be violated if a constant term is included in the regression equation (Brooks and Tsolacos, 2010). This assumption is automatically fulfilled as Stata includes a constant term in all regressions.

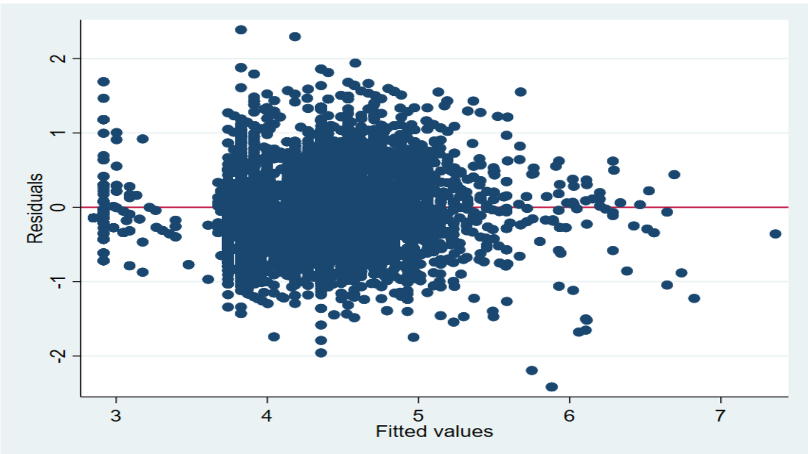
Assumption 2: Homoscedasticity $Var(\varepsilon t) = \sigma < \infty$

Second, to check whether the residuals are homoscedastic the Bruesch-Pagan/Cook-Weisberg is executed on Stata. The null hypothesis is that the variance of the errors is constant. The null hypothesis is rejected as the p-value is below 0.05 (0.000). This implies that the variance of the errors is not constant. Hence, robust standard errors are used in all OLS models to comply to the assumption.

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance
Variables: fitted values of log_price

chi2(1) = 43.97
Prob > chi2 = 0.0000



Assumption 3 : No Autocorrelation $Cov(\varepsilon i, \varepsilon j) = 0$ for $i = j$

Thirdly, it is assumed that the covariance between the error terms cross-sectionally is zero. This means that the error terms are uncorrelated. Model (5) considers this notion by including clustered standard errors.

Assumption 4 : No multicollinearity exists among the independent variables Cov (εt, xt) = 0

Fourthly, this assumption checks whether there is multicollinearity between the variables. Normally values below 10 are appropriate (Chen&Rotschield,2010). However , the distance intervals within 2 km does have VIF value between 5 and 8 which are a sign of multicollinearity. A large chuck of the Airbnb listings is located in the central neighborhood. Excluding the Neighborhood dummies lower the VIF values below 5 for all distance intervals.

Model (2)

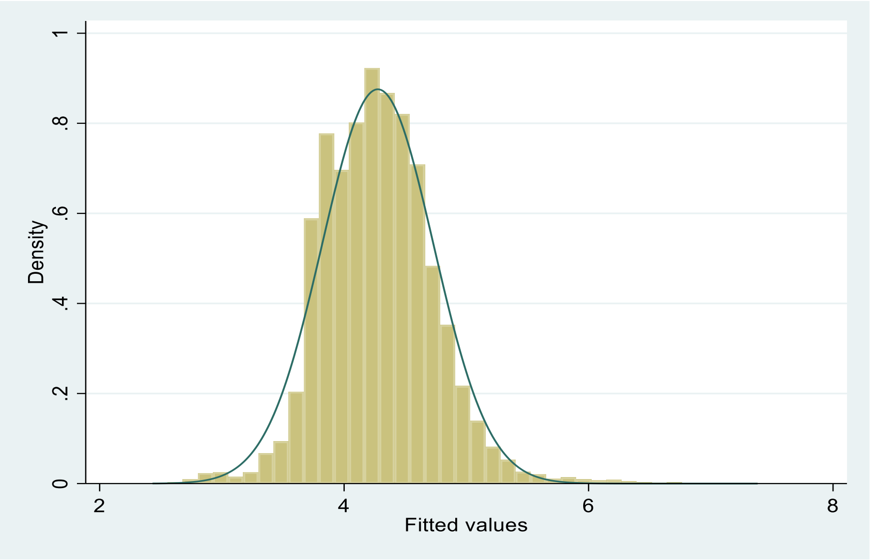
Variable	VIF	1/VIF
Bathrooms	2.21	0.451914
Bedrooms	3.30	0.302871
Accommodates	3.54	0.282500
Room Type		
2	1.48	0.676128
3	1.07	0.936270
Rental Policy		
2	1.39	0.717249
3	1.44	0.692367
Review score	1.18	0.846466
Reviews per month	1.14	0.873764
Superhost	1.23	0.815875
Host listings	1.10	0.912240
Nearest TA < 0,25 km	5.38	0.185979
Nearest TA < 0,50 km	7.52	0.133017
Nearest TA < 0,75 km	6.36	0.157215
Nearest TA < 1 km	5.69	0.175810
Nearest TA < 2 km	6.35	0.157388
Nearest TA < 3 km	3.63	0.275444
Nearest TA < 4 km	2.47	0.404673
Nearest TA < 5 km	1.73	0.577109
PA space	1.91	0.524735
Neighborhood		
2	1.48	0.675461
3	1.40	0.714925
4	1.57	0.635961
5	1.28	0.780064
6	1.90	0.526094
7	1.08	0.927751
8	1.89	0.529224
9	1.62	0.618932
10	1.43	0.698048
11	1.80	0.554942
12	1.22	0.817160
13	1.31	0.760676
14	1.29	0.772870
High density area	1.37	0.731844
Mean VIF	2.38	

Model (3)

Variable	VIF	1/VIF
Bathrooms	2.21	0.452594
Bedrooms	3.29	0.303750
Accommodates	3.52	0.284231
Room Type		
2	1.45	0.688280
3	1.06	0.945198
Rental Policy		
2	1.17	0.719415
3	1.44	0.694363
Review score	1.17	0.851842
Reviews per month	1.12	0.890994
Superhost	1.22	0.818293
Host listings	1.10	0.912972
Nearest TA < 0,25 km	3.09	0.323113
Nearest TA < 0,50 km	4.02	0.248733
Nearest TA < 0,75 km	3.27	0.305613
Nearest TA < 1 km	2.96	0.337551
Nearest TA < 2 km	3.66	0.272865
Nearest TA < 3 km	2.75	0.363976
Nearest TA < 4 km	2.96	0.337551
Nearest TA < 5 km	1.57	0.635372
PA space	1.81	0.553489
Mean VIF	2.21	

Assumption 5 : Normality εt N(0, σ2)

Filthy, this assumption is not per se needed for the validity of the OLS method to be BLUE. Nevertheless, the normality of residuals is tested by a histogram of the residuals. The residuals are assumed normal as can be seen in the figure below.



Appendix E: Entire Homes

	(4) Log Listing price
Bathrooms	0.180***
	(0.0119)
Bedrooms	0.0813***
	(0.00878)
Accommodates	0.0530***
	(0.00389)
Rental Policy = Moderate	0.0364***
	(0.00999)
Rental Policy = Strict	0.0363***
	(0.0126)
Review scores	0.00633***
	(0.000751)
Reviews per month	-0.0372***
	(0.00278)
Superhost	0.0437***
	(0.00979)
Host listings count	- 0.000933***
	(0.000306)
Nearest TA < 0,25 km	0.492***
	(0.0341)
Nearest TA < 0,5 km	0.456***
	(0.0324)
Nearest TA < 0,75 km	0.439***
	(0.0319)
Nearest TA < 1 km	0.338***
	(0.0317)
Nearest TA < 2 km	0.314***
	(0.0287)
Nearest TA < 3 km	0.204***
	(0.0255)
Nearest TA < 4 km	0.0829***
	(0.0273)
Nearest TA < 5 km	0.0893***
	(0.0313)
PA space	0.153***
	(0.0128)
Constant	2.952***
	(0.0747)
Neighborhood dummies	Yes
Observations	6,869
R-squared	0.562

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

Appendix F: Private Rooms

	(1)
	Log price
Bathrooms	-0.140***
	(0.0242)
Bedrooms	-0.000269
	(0.0247)
Accommodates	0.122***
	(0.0102)
Reviews per month	-0.0636***
	(0.00391)
Review score	0.00404***
	(0.001000)
Rental Policy = Moderate	0.0352**
	(0.0152)
Rental Policy = Strict	-0.0433*
	(0.0231)
Nearest TA < 0,25 km	0.486***
	(0.0563)
Nearest TA < 0,5 km	0.497***
	(0.0505)
Nearest TA < 0,75 km	0.464***
	(0.0489)
Nearest TA < 1 km	0.380***
	(0.0495)
Nearest TA < 2 km	0.336***
	(0.0418)
Nearest TA < 3 km	0.210***
	(0.0385)
Nearest TA < 4 km	0.107***
	(0.0377)
Nearest TA < 5 km	0.0250
	(0.0462)
PA Space	0.0896***
	(0.0250)
Constant	3.245***
	(0.111)
Neighborhood dummies	Yes
Observations	3,065
R-squared	0.378

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

Appendix G: Quantile regression entire homes

	(1)	(2)	(3)	(4)	(5)
	q10	q30	q50	q70	q90
Bathrooms	0.125***	0.157***	0.181***	0.198***	0.269***
	(0.0141)	(0.0188)	(0.0133)	(0.0116)	(0.0238)
Bedrooms	0.0391***	0.0670***	0.0796***	0.0912***	0.103***
	(0.0133)	(0.0119)	(0.0107)	(0.0124)	(0.0145)
Accommodates	0.0654***	0.0558***	0.0558***	0.0546***	0.0484***
	(0.00517)	(0.00496)	(0.00551)	(0.00619)	(0.00724)
Rental Policy = Moderate	0.0363**	0.0307***	0.0331***	0.0172	0.0363**
	(0.0153)	(0.00911)	(0.00975)	(0.0105)	(0.0161)
Rental Policy = Strict	0.0304*	0.0355**	0.0331**	0.0404***	0.0253
	(0.0175)	(0.0172)	(0.0153)	(0.0119)	(0.0182)
Review Score	0.00846***	0.00673***	0.00680***	0.00750***	0.00549***
	(0.00131)	(0.000885)	(0.000652)	(0.00101)	(0.00129)
Reviews per month	-0.0345***	-0.0343***	-0.0356***	-0.0359***	-0.0342***
	(0.00348)	(0.00258)	(0.00237)	(0.00226)	(0.00525)
Superhost	0.0319**	0.0375***	0.0363***	0.0283***	0.0425
	(0.0152)	(0.00894)	(0.00887)	(0.00833)	(0.0277)
Host listings count	-0.00364***	-0.000743*	-8.70e-05	-6.04e-05	0.000724
	(0.000471)	(0.000403)	(0.000408)	(0.000403)	(0.000800)
Nearest TA < 0,25 km	0.507***	0.492***	0.495***	0.514***	0.472***
	(0.0493)	(0.0414)	(0.0335)	(0.0402)	(0.0444)
Nearest TA < 0,5 km	0.459***	0.447***	0.433***	0.468***	0.464***
	(0.0424)	(0.0382)	(0.0246)	(0.0362)	(0.0490)
Nearest TA < 0,75 km	0.420***	0.434***	0.443***	0.474***	0.379***
	(0.0483)	(0.0388)	(0.0234)	(0.0348)	(0.0401)
Nearest TA < 1 km	0.361***	0.331***	0.347***	0.383***	0.282***
	(0.0489)	(0.0372)	(0.0289)	(0.0384)	(0.0519)
Nearest TA < 2 km	0.324***	0.316***	0.316***	0.332***	0.244***
	(0.0489)	(0.0310)	(0.0188)	(0.0238)	(0.0362)
Nearest TA < 3 km	0.236***	0.200***	0.208***	0.216***	0.130***
	(0.0417)	(0.0324)	(0.0164)	(0.0240)	(0.0418)
Nearest TA < 4 km	0.0968***	0.0799**	0.0960***	0.0779***	0.0142
	(0.0334)	(0.0316)	(0.0220)	(0.0254)	(0.0396)
Nearest TA < 5 km	0.136***	0.119***	0.0903***	0.0793	0.0192
	(0.0515)	(0.0273)	(0.0232)	(0.0492)	(0.0710)
PA Space	0.0944***	0.134***	0.155***	0.165***	0.163***
	(0.0191)	(0.0194)	(0.0178)	(0.0149)	(0.0186)
Constant	2.453***	2.786***	2.879***	2.954***	3.363***
	(0.144)	(0.0887)	(0.0604)	(0.0975)	(0.133)
Neighborhood dummies	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.27	0.32	0.35	0.37	0.4
Observations	6,869	6,869	6,869	6,869	6,869

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1