The effect of Airbnb activity on residential real estate values and livability: The case for the Netherlands

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Abstract: This paper attempts to examine the relationships between Airbnb activity, subjective livability and residential real estate values. Specifically, this research answers the following research question: Does subjective livability have a mediating effect on the relationship between Airbnb activity and residential real estate values? To answer the research question, the mediation model proposed by Baron and Kenny is used to examine the relationships. The results indicate that Airbnb activity has a positive effect on residential real estate values. Specifically, a 1 percent increase in Airbnb activity leads to a 0.038 percent increase in residential real estate values. Furthermore, the results suggest that Airbnb activity has a negative effect on subjective livability and subsequently subjective livability has a positive effect on residential real estate values. Therefore, it follows that subjective livability acts as a mediator between Airbnb activity and residential real estate values. Subjective livability dampens the total effect of Airbnb activity on residential real estate values by 47.3 percent.

Keywords: *Airbnb, Residential Real Estate Values, Livability, Mediation, Hedonic Pricing Method, Netherlands, Amsterdam*

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INTRODUCTION

In 2007, Brian Chesky and Joe Gebbia were living in an apartment in San Francisco. Since rents were high in San Francisco and they were struggling to pay for their apartment, they came up with the idea to put an air mattress in their living room and turn it into a bed and breakfast. They launched a website to facilitate bookings in August of 2008 and the idea of Airbnb was born.

Over the years, Airbnb's popularity skyrocketed and grew to be the biggest short-term rental broker of the world (Gutiérrez, García-Palomares, Romanillos and Salas-Olmedo, 2017). As of today, Airbnb facilitated more than 800 million guest arrivals worldwide, lists more than seven million listings in over 220 countries and 100.000 cities and accommodates more than two million people across the world every day (Airbnb, 2020a). However, unlike conventional hotels, Airbnb does not own or manage any properties itself, but merely acts as a broker between property owners wishing to rent out space on the short-term rental market and tourists looking for accommodation. While Airbnb is not the only short-term rental company on the Dutch market, it is certainly the market leader in this particular domain (Guttentag, 2015; Oskam and Boswijk, 2016). What effect these short-term rentals have on livability is subject to debate.

While offering private housing as tourist accommodation through online platforms like Airbnb might be a lucrative source of income to property owners, many actors raised their concerns about the rapid growth of Airbnb and other online platforms that facilitate the sharing economy. Firstly, as many property owners could potentially earn more money by offering accommodation to tourists than to long-term tenants, some of them will choose to extract the property from the long-term rental market. This decreases the long-term rental market stock and contributes to the growing housing affordability problem in many cities, such as Los Angeles, London and Amsterdam (Barker, 2020; Guttentag, 2018). Secondly, residents are worried that the increase of Airbnb activity in their neighborhood will damage the sense of community and the "feel of the neighborhood", due to the increasing number of strangers (Guttentag, 2018). Lastly, as in many cases the owner of the property is not actually present at the property, tourists could be involved in anti-social behavior, such as excessive noise, vandalism, disturbance, littering and crime. This could have an effect on the livability of the neighborhood (Guttentag, 2018). The aforementioned effects of Airbnb activity on livability could possibly also have an effect on residential real estate values (D'Acci, 2014).

Local governments worry that this new form of tourist accommodation has an effect on livability and consequently housing affordability of a certain area. Disruptive technologies often outpace applicable regulations, resulting in concerns such as general legality or taxation (Carrns, 2013; Song, 2011; Wolverton, 2002). Therefore, in many cities around the world, short-term rental is legally restricted (Dann et al., 2019). In Paris, for example, rentals of less than 12 months are prohibited without a license (Huet, 2021). However, the municipality of Amsterdam first embraced short-term rentals. The municipality saw Airbnb as a way to promote tourism, while tourism can bring economic and social benefits to a city (Bahceli, 2015; Kok, 2015). During the financial and housing crisis between 2007 and 2010, the municipality thought that allowing short-term rentals would help home owners to pay for their mortgages. The municipality also wished to increase visitor numbers and spread tourist spending over more neighborhoods so that more residents could benefit of the increasing number of tourists in their city (Oskam and Boswijk, 2016). Thus, the municipality of Amsterdam did not want to be too stringent by prohibiting all short-term rental activity in their city. Instead of prohibiting short-term rental activity, the municipality of Amsterdam and Airbnb sat down at the table and discussed what would be best for all parties involved. In the end, Amsterdam passed "Airbnb friendly legislation" (van de Glind and van Sprang, 2015). They agreed that from the 1st of January, 2017, entire homes could only be rented for a maximum of 60 days per year if the home-owner did not have a license (Dann et al., 2019).

In the early years of Airbnb, things worked out. However, due to the steep tourism growth in general and the popularity of short-term rentals in particular, many investors saw the potential to earn great amounts of money by transforming long-term rentals to short-term rentals. They started building a portfolio of Airbnb properties in the most popular neighborhoods, driving up real estate values and rental prices (Oskam and Boswijk, 2016). Due to the rising residential real estate values and the upward pressure on livability in some neighborhoods in Amsterdam, the municipality decided to intervene. The current situation was not sustainable in the long run. Because the negative effects of short-term rentals became more visible, the municipality eventually decreased the number of days entire homes without a license could be rented to 30 days per year (Municipality of Amsterdam, 2020a). While the municipality tightened its the reins, research about the effect of short-term rentals on livability and consequently housing affordability has not been extensive.

The purpose of this paper is to provide quantitative statistical evidence of the relationship between Airbnb activity, subjective livability and residential real estate values. While previous research on the relationship between Airbnb activity and livability has taken a qualitative approach, Jordan and Moore (2018) suggest that future research should take a quantitative approach to increase the validity and reliability of previous literature on the relationship between Airbnb activity and subjective livability. Furthermore, some research regarding the relationship between Airbnb activity and residential real estate values has been done. However, the potential mediating effect of subjective livability has not yet been included in this equation. Subsequently, the aim of this paper is to answer the following research question:

Does subjective livability have a mediating effect on the relationship between Airbnb activity and residential real estate values?

To answer the research question, a mix of several different methods has been used. First, a hedonic pricing model has been used to dissect the residential real estate value and find the effect of Airbnb activity and subjective livability on residential real estate values. The hedonic pricing model takes into account the intrinsic characteristics of the property, extrinsic characteristics of the property and time fixed effects. Second, the mediation model proposed by Baron and Kenny (1986) is used to calculate the mediating effect of subjective livability. At last, IV regression is used to mitigate the possibility of endogeneity between residential Airbnb activity on one side and residential real estate values and subjective livability on the other side.

This study examines the municipality of Amsterdam and uses multiple datasets from different sources. Data on Airbnb has been provided by InsideAirbnb, an independent non-profit organization led by Murray Cox. Residential real estate data has been provided by the NVM, the Dutch association of real estate agents. Data on subjective livability and other neighborhood characteristics has been obtained from several governmental bodies, such as the Municipality of Amsterdam and the Dutch Central Bureau of Statistics (CBS).

The results of this study indicate that Airbnb has a direct positive effect on residential real estate values. For every 1 percent increase in Airbnb activity, residential real estate values increase by 0.038 percent. The results also imply that Airbnb has a negative effect on subjective livability. For every 1 percent increase in Airbnb activity, subjective livability decreases with 0.00321 units. Furthermore, the results indicate that subjective livability has a positive effect on residential real estate values. For every one-unit increase in subjective livability, residential real estate values increase by 5.76 percent. The above suggests that subjective livability mediates the direct effect of Airbnb activity on residential real estate values and that the indirect effect of Airbnb activity on residential real estate values – through subjective livability as the mediator – dampens the direct effect by 47.30 percent.

The remainder of this paper is organized as follows. Section 2 reviews previous research regarding Airbnb, livability and residential real estate values. Furthermore, the hypotheses are formulated. Section 3 outlines the methods used to empirically test the hypotheses. Section 4 describes the data used and the exploratory analysis. Section 5 presents the results and section 6 discusses some considerations regarding the robustness of the results. At last, section 7 outlines the conclusion, discusses the practical implications and limitations of this research and suggests options for future research.

LITERATURE REVIEW

The founders of Airbnb initially started to rent out an air mattress in their own living room as a way to support their rent payment. Even after launching the Airbnb website in 2008, the focus was to attract like-minded people who also wanted to rent out unused or underused space within their already occupied homes (Airbnb, 2020a). With that in mind, Airbnb could be seen as being part of the so-called sharing economy. They often use terms such as "car sharing" and "home sharing", although it would be more accurate to call it short-term rental activities (Belk, 2014). While Airbnb continues to argue that they are part of the sharing economy, their business practices say otherwise. Within one year of the website's official launch, Airbnb expanded its services beyond unused or underused space, such as a spare bedroom, giving people the option to list entire apartments, houses and even vacation rentals (Airbnb, 2020a). To get a better understanding of the reason Airbnb vigorously wants to be part of the sharing economy and if their claim is correct, we take a closer look at literature regarding sharing and the sharing economy.

Sharing

Sharing is a human habit that dates back to the dawn of time. People share in many different contexts, such as sharing a picture on Facebook, sharing a secret with a good friend or sharing experiences (Frenken and Schor, 2017). In an economic sense, sharing can be described as two or more people enjoying the advantages and carrying the disadvantages that come with the ownership of something. When something is shared, it is not mine or yours, but it can be identified as ours (Belk, 2007).

In economics, the ideal form of exchange is commodity exchange. However, sharing is a type of distribution that differs from commodity exchange (Belk, 2007). Commodity exchange involves the exchange of goods and services for money, whereas when something is shared, we do not expect money in exchange. Sharing can thus only happen in the absence of a market transaction (Oskam and Boswijk, 2016).

One of the reasons that short-term rental became successful, is the fact that consumers changed their preference from ownership to sharing. In Western countries, a major transition has taken place, from agricultural and industrial production with a focus on product ownership to a service economy, where experiences and temporary access to goods and services are more important than ownership. In other words, in Western countries, the economy is dematerializing (Oskam and Boswijk, 2016; Bardhi and Eckhardt, 2012; Herman, Ardekani and Ausubel, 1990).

Sharing occurred more frequently among family, relatives and friends than among strangers (Belk, 2014). With the advent of Web 2.0 internet technologies, where the internet became a means of communication and virtually anyone could share information on the internet with others, this started to change (Belk, 2007). The internet has created numerous new ways to share and makes previous forms of sharing possible on a larger scale (Belk, 2014). Airbnb and other short-term rental platforms also make use of Web 2.0 internet technologies. People that have unused or underused space can, all by themselves, place an advertisement on one of the short-term rental platforms to notify people who are looking for a place to sleep that space is available for rent (Belk, 2014; Guttentag, 2015).

Sharing economy

Until today, there is no consensus on the definition of the sharing economy (Belk, 2014; Villari, 2018; Curtis and Lehner, 2019; Ertz and Leblanc-Proulx, 2018; Gurău and Ranchhod, 2020) and various terms are used to define the same concept, such as collaborative economy, peer economy and access-based economy (Mont et al., 2020; Villari, 2018). In this research, sharing economy is defined as an economic model in which access to resources is more important than ownership and consumers act both as provider and receiver of unused or underused resources on community-based online platforms enabled by Web 2.0 technologies (Prayag and Ozanne, 2018; Hamari, Sjöklint and Ukkonen, 2015; Meelen en Frenken, 2015; Botsman, 2015). To get a better understanding of the definition of the sharing economy, the definition can be dissected in the following characteristics:

- The sharing economy is based on online platforms which are enabled by Web 2.0 technologies (Hamari et al., 2015). With the help of Web 2.0 technologies virtually anyone can create content on the Internet by simply uploading it to a website. Airbnb and other short-term rental platforms make use of these Web 2.0 technologies (O'Reilly, 2007; Shelly and Frydenberg, 2011); consumers can advertise their unused or underused space on one of these platforms to attract potential guests.
- In the sharing economy, consumers do not only receive goods and services, but are also able to supply goods and services to the market. Consumers therefore fulfil a dual role of provider and receiver (Manzini, 2015). Web 2.0 technologies made these peer-to-peer transactions possible (O'Reilly, 2007; Shelly and Frydenberg, 2011).
- Most researchers' definition of the sharing economy includes some demarcation on which resources are included. Meelen and Frenken (2015) include underutilized physical assets and idle capacity, while Barron, Kung and Proserpio (2018) include excess capacity in their definition of the sharing economy. Later on in this research, it is discussed why this is one of the problems when it comes to labelling short-term rentals as sharing economy and why short-term rentals possibly have an effect on residential real estate values and subjective livability.

- What could be one of the most important characteristics of the success of the sharing economy is the fact that sharing economy businesses like Airbnb were able to capitalize on the changing trend from product ownership to experiences and access to resources (Oskam and Boswijk, 2016). Instead of owning a vacation home, which is bound by its geographical location, in this day and age, tourists want to explore more than one place and experience the local culture. Staying with locals in their home is a new way to experience that local culture (Guttentag, 2015).

Airbnb: A true sharing economy business?

Platforms like Airbnb position themselves as being part of the sharing economy, because sharing has a positive symbolic value (Frenken and Schor, 2017). However, many researchers question the legitimacy of Airbnb's view. Some researchers even argue that Airbnb is just offering an "innovative rental practice" (Lagonigro, Martori and Apparicio, 2020, p.2; Arias Sans and Quaglieri, 2016; Kallis, 2014; Lee, 2016). Opponents argue that Airbnb is exploiting its users and only serve their own self-interest and that of their investors (Mallinson et al., 2020). After the launch of the platform in 2008, Airbnb initially focused on attracting people that wanted to rent unused or underused space within their already occupied homes, such as a spare bedroom. This quickly changed; within one year of the website's official launch, Airbnb expanded its services beyond unused and underused space, giving people the option to advertise apartments, houses and vacation rentals (Airbnb, 2020a).

Consequently, professional landlords and other professional parties saw the opportunity to earn more money with their rentals by renting them on the short-term rental market rather than the long-term rental market (Perren and Kozinets, 2018). This can be substantiated by the fact that many Airbnb hosts have more than one listing. For example, Arias Sans (2015, cited in Oskam and Boswijk, 2016, p. 29) finds that 30 percent of Barcelona's entire home listings is controlled by 2.5 percent of hosts and 60 percent of entire home listings is offered by hosts with multiple listings. The same is true for Sydney, where more than 30 percent of listings is offered by hosts with more than one listing (Gurran and Phibbs, 2017).

Additionally, there seems to be evidence that investors are buying property with the primary goal to rent it out on Airbnb (Gutiérrez et al., 2017). For example, Samaan (2015) finds that 64 percent of Airbnb listings in Los Angeles are never occupied by their owners and are permanently listed on the Airbnb platform. Furthermore, Gurran and Phibbs (2017) find that, in Sydney, investors are acquiring houses and transform them into permanent Airbnb listings. Gyódi (2019) also finds that the short-term rental markets of Paris, Barcelona, Berlin and Warsaw are dominated by professional host listings. Listings which can be categorized as 'real' sharing economy only constitute 11 to 49.5 percent of the total listings in the above-mentioned cities.

As can be concluded, in some cities only a small portion of all Airbnb listings can be considered being part of the sharing economy (Gyódi, 2019). In this sense, the un-utilization of a spare room or the under-utilization of an entire home on one side and the year-round rental of entire houses on the other side is the main dividing line between 'real' sharing economy services and commercial business-to-consumer services (Gyódi, 2019). For Airbnb, it is a logical choice to allow hosts to operate permanent rentals. Airbnb earns a percentage of the total value of each rental agreement (Airbnb, 2020b). Expanding their services to allow permanent rentals could therefore only help them grow.

Unfortunately, Airbnb has a range of impacts on its environment, namely on the larger economy, society and governance. These impacts could be substantial and long-lasting (Mallinson et al., 2020). Some of the suspected impacts include increasing residential real estate values, decreasing tourism tax revenues, accelerated gentrification and overcrowding (Prayag and Ozanne, 2018). However, current literature has only examined a small number of possible consequences and even less studies have attempted to empirically estimate impacts (Heo, 2016; Zervas, Prosperpio and Byers, 2017). This research mainly focusses on the effect of Airbnb activity on residential real estate values and subjective livability and the effect of subjective livability on residential real estate values. The current field of literature has explored the impacts of Airbnb listings on housing and neighborhoods, but according to Gurran and Phibbs (2017) this field of research is still in its infancy. Dann, Teubner and Weinhardt (2019) further mentioned that it is not justifiable to generalize the outcomes of 'local' studies on Airbnb to other cities and countries, let alone the entire platform. It is thus important to continue to examine new locations.

Airbnb activity and residential real estate values

Before the arrival of Airbnb and other short-term rental platforms, the short-term rental market and the long-term rental market mostly operated independently from each other. With traditional hotels and hostels serving the market for short-term rentals and little possibilities for owners of long-term rentals to switch to the short-term rental market, an equilibrium was in place. With the advent of Airbnb, home owners suddenly had the choice to offer their rental on the short-term rental market. Consequently, a fraction of long-term rental stock reallocated to the short-term rental market. Since housing supply is inelastic, such reallocation could lead to increasing rental prices (Calder-Wang, 2020; Chang, 2020). Lee (2016) further mentions that sales prices could also increase if property owners decide to use their property on the short-term rental market instead of selling it. Additionally, as mentioned earlier, investors are eager to buy up properties which were previously used by their owner-occupiers with the sole purpose of renting the unit on Airbnb (Gutiérrez et al., 2017).

Some research about the relationship between Airbnb and the residential real estate market has been done. Schäfer and Braun (2016) find that, in Berlin, many apartments are being used for short-term rental and that rent growth is higher in neighborhoods which have more short-term rentals. In Los Angeles, Lee (2016) finds that Airbnb reduced the housing supply with 7,316 units. Gurran and Phibbs (2017) further find that in Sydney, rents are under increased pressure from Airbnb and the availability of long-term rentals around major tourist areas is decreasing.

More recent research focused on quantifying the effect of Airbnb on rents and residential real estate values. Horn and Merante (2017) argue that the number of Airbnb listings has a positive effect on rents and found that asking rents increased with 0.4 percent in Boston if Airbnb activity increased with one standard deviation. Barron et al. (2018) examined US neighborhoods and found that Airbnb increased rent prices with 0.42 percent and sales prices with 0.76 percent. In Taiwan's urban areas, a one hundred unit increase of the total number of Airbnb listings increases nearby rental prices with 0.83 percent (Chang, 2020). Closer to home, Garcia-López et al. (2020) find that Airbnb activity has raised Barcelona's rents 1.9 percent and sales prices with 4.6 percent. The impact is even bigger in neighborhoods where Airbnb activity is most substantial; rents in those neighborhoods grew with 7 percent and sales prices increased with 17 percent.

Although previous research finds different magnitudes of effect, in all instances, the effect of Airbnb activity on residential real estate values is positive. We thus suspect that Airbnb activity has a positive effect on residential real estate values.

Hypothesis 1: Airbnb activity increases residential real estate values.

Livability

Livability has been a subject of interest for a substantial amount of time as it is an intriguing topic. Livable places create the right circumstances for people to be happy (Okulicz-Kozaryn, 2013). Livability is also vital for businesses as happy people are better employees (Lyubomirsky, King and Diener, 2005). Likewise, livability is crucial for municipalities as livable places attract valuable employees and businesses, and the economic activities that these businesses and employees bring are the cornerstone to urban growth (Economist 2011a, b).

When most people describe a livable city, they almost describe a perfect situation which can be referred to as utopia; a livable city with an abundance of services and facilities to accommodate its residents, enough opportunities for self-fulfillment, such as work, education and leisure activities, an abundance of green space and which is a safe place to live, work and relax. Additionally, a livable city should be economically sound and have a positive effect on the environment (Kaal, 2011; Hamilton and Atkins, 2008).

Over the last couple of years, the term livability has been used extensively by researchers of various disciplines, cultures, and with different objectives. Consequently, different studies explain livability in different ways and with different dimensions. The different dimensions used reflect the researchers common understanding of living environment quality (Leby and Hashim, 2010). While most popular media and news outlets regard the term livability self-explanatory, within academic literature, there is significant discussion about the definition and generalizability of the concept (Kashef, 2016). Although adding to the discussion of defining the concept of livability is not one of the objectives of this paper, it is essential to tie a definition to the concept so that the reader of this paper is on the same page as the writer. In this paper, the definition in Lloyd, Fullagar and Reid (2016, p. 345) is followed, which states that livability is "an individual's perspective and their subjective evaluation of the quality of both tangible and intangible features of place."

The measurement of livability

There are essentially two strands of research on the measurement of livability. Livability can be measured objectively or subjectively (Kaal, 2011). How researchers measure livability could be based on their theoretical background. Researchers with an economics background would probably consider a measure of wealth, such as Gross Domestic Product (GDP), to measure the degree of livability of a country, whereas researchers with a social science background would consider subjective measures, such as subjective well-being, happiness or life satisfaction (Cummins, 2000; Uysal et al., 2016). To get a better understanding of the differences between objective and subjective measures of livability, a closer look will be given to both types of measures.

When one considers an objective measure of livability, one quickly arrives at composite indicators of livability. Numerous composite indicators of livability have been constructed in light of governmental policy evaluation. These composite indicators have a range of indicators chosen by government officials with the intention to compare the objective situation of a certain area with policy targets or to highlight possible concerns (Nakanishi et al., 2005, cited in Doi, Kii and Nakanishi, 2008, p. 1102). The mercer index, the EIU livability ranking, the OECD BLI are only three examples of the numerous composite indicators of livability that exist (Kashef, 2016). These composite indicators all take a different approach in the measurement of livability, but what all of these composite indicators have in common is the fact that they try to capture livability objectively, without taking the subjective part into consideration (Okulicz-Kozaryn, 2013). Ultimately, composite indicators of livability are appealing to use, since they paint an objective and quantifiable picture of the living conditions and consist of elements the local government can directly affect (QUT, 2009, cited by Lloyd et al., 2016, p. 346).

Although some researchers conclude that composite indicators of livability are the ideal measurement tool, due to the fact that local governments can directly affect its components, it would be fair to ask if a composite indicator is also the right measurement tool for this research. Composite indicators of livability consisting of objective indicators are often criticized, because they take little notice of the way local residents perceive their everyday life (Vine, 2012, cited by Lloyd et al., 2016, p. 346; Woolcock, 2009, cited by Lloyd et al., 2016, p. 347). This does not mean that the quality of the living environment does not have an effect on the livability of residents, but that a neighborhood which scores high on a composite indicator of objective livability variables is not necessarily livable in the eyes of the residents that live in that neighborhood (Norouzian-Maleki et al., 2015).

Likewise, it is often implied that the objective and subjective indicators of livability have a connection. Schneider (1975) researched the relationship between life satisfaction and objective indicators of livability and found a weak correlation of 0.4 between the two types of indicators. Pacione (2003) examined multiple papers on the relationship between objective and subjective indicators of livability and found some research highlighting a strong relationship between the two sets of indicators, while other research only found a weak relationship or no relationship at all.

Although the objective situation potentially influences subjective livability, it does not explain why two people in the same neighborhood experience the livability of the neighborhood differently (Okulicz-Kozaryn, 2013). However, this is not surprising as individuals' perceptions of an objective situation are influenced by their current situation, their attitudes and their prior experiences (Campbell, Converse and Rodgers, 1976). Due to those perceptions, it is possible for those individuals to be in an objectively better situation than others, such as being in a city with good employment, health care and leisure opportunities, but still subjectively feel that their livability is lower than other people in that city or other cities (Schneider, 1975). Furthermore, people all have differing needs and are raised with varying norms and values. This results in contrasting views about how a livable neighborhood – and more broadly, a livable society – should look like (Leby and Hashim, 2010). Highlighting an example for a neighborhood characteristic, one could think of a children's playground. People without children living in that neighborhood probably find no use for the playground and might even experience negative effects due to screaming children in their "backyard". People with children could value the playground, as their children have the opportunity to safely play outside (Leby and Hashim, 2010). Additionally, livability does not only consist of the above-mentioned tangible features, but should also include intangible features, such as sense of place, local identity and social networks (Leby and Hashim, 2010).

From the above, it can be concluded that objective indicators of livability do not capture the important subjective feelings of the residents about the livability of their city or neighborhood. Using subjective indicators of livability has the benefit of capturing how local residents experience their surroundings instead of what researchers think is important to these local residents (Okulicz-Kozaryn, 2013). By using a subjective measure of livability, it essentially takes away one more factor between what is defined as important in the literature and what residents find important themselves (Schneider, 1975). Ultimately, local residents should be the judge when it comes to their own livability (Hacker, 2010). Groot (1967, cited by Kaal, 2011, p. 537) even argues that it is not possible for a researcher to provide an entirely objective assessment of the livability of a place based on a set of objective indicators. This could be due to the fact that livability is a subjective concept. That is, livability is about feelings, perceptions and attitudes (Tsaur, Lin and Lin, 2006). What thus constitutes a livable city or neighborhood, is very personal as every human being has a different set of feelings, perceptions, attitudes, aspirations, expectations, norms and values. Each resident thus sees their neighborhood or city through their subjective filter (Buys, Vine and Miller, 2013). It can thus be concluded that it would be more sensible to take a subjective approach to the measurement of livability.

Airbnb activity and subjective livability

In recent years, Airbnb has been under a lot of scrutiny. In Amsterdam, new legislation was introduced, which stated that from January 1st, 2017, entire homes could only be rented for a maximum of 60 days per year if the home-owner did not have a license (Dann et al., 2019). As this measure was not enough to solve the problems existing between residents and Airbnb-visitors, the municipality eventually decreased the number of days entire homes without a license could be rented to 30 days per year (Municipality of Amsterdam, 2020a). Last year, the municipality of Amsterdam even introduced a new licensing system for home owners who wanted to rent their home on Airbnb (Municipality of Amsterdam, 2020b). One of the reasons the municipality of Amsterdam is taking more stringent measures against the expansion of Airbnb are the numerous complaints by residents of Amsterdam about Airbnb and other tourism-related activity. Laurens Ivens, alderman of Amsterdam, stated that more than 80 percent of residents living in the city center experience frequent nuisance from short-term rentals (Westerveld, 2020).

It is not surprising that residents experience nuisance from short-term rentals. Tourists often have a deviating day and night rhythm from residents– tourists typically enjoy the night and return to their accommodation late (Westerveld, 2020). Residents go to bed earlier, while they have to be bright and early at work the next day. A couple of years ago, this deviation was not a problem at all. Tourists mainly stayed in hotels and hostels, which are located in commercial buildings and away from residential buildings. Through the advent of Airbnb and other short-term rental platforms, this changed. Over the years, more and more Airbnb listings came about and most of them are located in residential buildings. This has led to (unwanted) exposure and interaction between residents and tourists (Jordan and Moore, 2018). The constant influx of new people in a residential building or neighborhood can be bothersome to its residents and could have a wide array of externalities (Gottlieb, 2013). However, externalities are present with most economic activity. For example, in the Netherlands, car owners pay a hefty amount of tax on gas and car ownership. The government uses this tax income to minimize the negative externalities caused by car owners, such as placing barriers between a busy highway and a quiet neighborhood. By taxing the users of the highway, the producers of the negative externality essentially pay to minimize the effect of their economic activity. However, a problem occurs when there is no legislation in place to transfer the costs of negative externalities from the third party to the producer of the negative externality (Lazăr, 2018). The third party now experiences negative effects from another person's economic activity without the problem being solved or being compensated.

In the case of Airbnb and other short-term rental platforms, some research has been done about its effect on residents and their livability. Jordan and Moore (2018) conducted in-depth interviews with residents and other stakeholders of Hawai'i and found that residents perceive positive and negative effects from Airbnb and other short-term rental platforms. Most interviewees recognize the unprecedented positive economic value Airbnb has, but also mention that they experience increasing car traffic and overcrowding right at their doorstep. However, the most reported negative effect of short-term rentals was the loss of community sense. This is expected as tourists are effectively replacing residents, which leaves a smaller group of people to participate in community activities that foster that community sense (Chen, 2014; Pindell, 2009).

Gurran and Phibbs (2017) examine Sydney and find that an increasing number of residents experience negative effects by Airbnb. Members of the Owners Corporation Network mention that tourists staying in their residential building often show little concern for building security and rules. Additionally, Airbnb is being linked to excessive noise, intoxicated behavior, litter and parking issues. Residents also get the feeling of unease, as they constantly see new people in their building that are not familiar to them (Richardson, 2015, cited in Gurran and Phibbs, 2017, p. 87). It is further mentioned that problems, such as noise from parties and drunk people, are more likely to occur when larger groups of people stay at an Airbnb (Thomas, 2015, cited in Gurran and Phibbs, 2017, p. 85).

Nieuwland and van Melik (2018) researched multiple cities around the world and found that most respondents expressed their worries about nuisance, litter and parking. However, some of the problems vary by neighborhood. They also mention that the kind and severity of the problems is related to the type of short-term rental, with larger, professionally run short-term rentals generating the most issues. Additionally, some respondents mentioned a loss of culture.

Although some research about the effect of Airbnb on livability has been done, most of this research is qualitative of nature. Uysal et al. (2016) further mentions that the suspected link between tourism in general and the livability of the community should be further examined to empirically validate the above qualitative findings. To add strength to the growing literature on Airbnb and livability, the link between Airbnb and subjective livability will be quantitatively examined. From previous research it is expected that Airbnb has a negative effect on subjective livability.

Hypothesis 2: Airbnb activity decreases subjective livability.

Subjective livability and residential real estate values

Livability is a multidimensional concept which consists of multiple indicators. As mentioned above, the definition of Lloyd et al. (2016, p. 345) is followed, which means that livability consists of tangible and intangible features of a place. By dissecting livability into individual tangible and intangible features, it is possible to link the concept of livability to residential real estate values.

Extensive research has been done on the effect of tangible features on residential real estate values. For example, residential real estate values increase when there is an abundance of green space nearby. Tajima (2003) finds that property prices in Boston decrease by 6 percent when the distance to the nearest park doubles. Conway et al. (2008) finds that residential real estate values in downtown Los Angeles increase with 0.07 percent when the amount of green space increases with 1 percent. Residents also value accessibility. Using the hedonic pricing method, Schaerer et al. (2008) show that rent prices of centrally located houses in Geneva and Zurich are 9.1 percent and 10.5 percent higher than other houses, respectively. At the other end of the world, in Hong Kong, Hui et al. (2007) find that residential real estate values decrease with 0.8 percent for every minute increase in travel time to the Central Business District. However, living further away from the city center is not necessarily a problem. Good public transport to other parts of the city is also convenient and this can be shown by the increase in house prices when public transport is nearby. Cervero and Kang (2011) find that house prices in Seoul increase by up to 10 percent when a bus stop is within 300m of the residence. House prices in Hong Kong which are located within 0.4 km of a railway station are 4.6 percent higher than average (Jim and Chen, 2009). Having reputable schools in the vicinity of their home is also valued by residents. Hui et al. (2007) find that property prices in Hong Kong increase by 0.1 percent for each additional reputable school in the district. Some tangible features of livability have a negative influence on residential real estate values. For example, Neupane and Gustavson (2008) find that property values in Sydney, Canada are 13 percent lower than average when a hazardous waste site is within 100 m of the property. Furthermore, houses in the proximity of O'Hare airport, Chicago were approximately 9 percent lower (McMillen, 2004). Other research on house prices in Portland suggests that houses located on a busy arterial road are 15 percent cheaper than houses that are located 500 feet from a busy arterial road (Polloni, 2019).

The effect of intangible features on residential real estate values has also been a subject of research interest. For example, residential real estate values are lower in areas with high noise levels. Bateman et al. (2001) find that residential real estate values in Glasgow decrease with 0.2 percent per dB. In Leiden, Netherlands, Luttik (2000) found that noise decreased house prices by 5 percent. Similarly, it has been proven that air pollution decreases residential real estate values. In Hong Kong, house prices are, on average, 1.3 percent higher if the house is located in a neighborhood where the annual average air pollution is 1 percent lower (Jim and Chen, 2009). Kim, Phipps and Anselin (2003) find that the willingness to pay for a 4 percent improvement of sulphur dioxide concentrations is 1.4 percent of the average residential real estate prices. Additionally, Colombo and Stanca (2014) argue that the willingness-to-pay of residents increases with €1150.- per year for relational amenities, such as spending time with friends.

The above individual indicators are only a few examples of indicators that are considered to be components of livability (D'Acci, 2014; Colombo and Stanca, 2014). Additionally, it can be concluded that these individual indicators are estimators of residential real estate values. Therefore, a link between residential real estate values and livability can be established. Residential real estate values can be determined by intrinsic and extrinsic characteristics. The intrinsic characteristics are all the characteristics of the residence that are strictly connected to that residence, such as the size, the quality and the construction year (D'Acci, 2014). These intrinsic characteristics differentiate residences that are located in the same area (Huang, Wu and Barry, 2010). After subtracting the value of the intrinsic characteristics of the residence, the residual value is equivalent to the monetary valuation of the extrinsic characteristics of the residence (i.e., livability). In other words, the value of the extrinsic characteristics of a residence is the quantification of the level of livability a resident could expect to get when the resident lives in that particular country, city, neighborhood and street (D'Acci, 2014).

The overall effect of livability on residential real estate values should not be taken lightly. D'acci (2014) examined residential real estate values of Turin, Italy and found that residential real estate values across the city varied 143 percent depending on the quality of the area that a particular residence is located in. This could be explained by the fact that people value certain aspects of the environment – such as the individual indicators mentioned above – and are willing to pay for those aspects (Colombo and Stanca, 2014).

Livability is a positive notion, which means that people value higher livability over lower livability. Living in a neighborhood which offers a high level of livability is considered positive. As the value of residential real estate is partly the quantification of the level of livability a resident could expect to get when that resident lives in that particular place, it is expected that livability is positively related to residential real estate values (Zhang et al., 2019; Colombo and Stanca, 2014).

Hypothesis 3: Subjective livability increases residential real estate values

The mediating effect of subjective livability

In the above sections, three hypotheses are formulated:

1. Airbnb activity increases residential real estate values;
2. Airbnb activity decreases subjective livability;
3. Subjective livability increases residential real estate values.

The suspected relationships between the three variables are displayed in Figure 1. Interesting to note is that the effect of Airbnb activity on residential real estate values could be divided into a direct and indirect effect. First, Airbnb activity directly increases residential real estate values. Second, Airbnb activity directly decreases subjective livability and subjective livability directly increases residential real estate values. Thus, Airbnb activity indirectly decreases residential real estate values through subjective livability. The direct effect of Airbnb activity on residential real estate values is positive, while the indirect effect of Airbnb activity on residential real estate values is negative. In other words, the indirect effect of Airbnb activity through subjective livability on

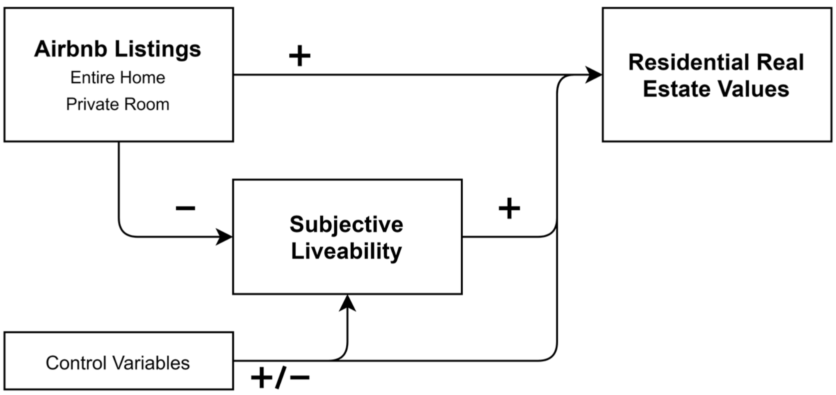

***Figure 1**: Conceptual model*

residential real estate values dampens the direct effect of Airbnb activity on residential real estate values. To conclude this research, the following hypothesis will be tested:

Hypothesis 4: The indirect effect of Airbnb activity through subjective livability on residential real estate values dampens the direct effect of Airbnb activity on residential real estate values.

METHODOLOGY

In this section, the methods used in this paper are set out. Firstly, the dependent variable in this research is the average neighborhood residential property value and can be determined by the hedonic pricing method. Secondly, this paper uses a fixed effects approach to control for differences in transaction price during the analysis period. Lastly, from previous literature, it is suspected that there exist multiple relationships between the variables Airbnb activity, subjective livability and residential real estate values. Therefore, a mediation model is used to see what the effects between all these variables are and what part of the total effect is direct and what part of the total effect is indirect.

The hedonic pricing method

Pricing goods can be a complicated undertaking, especially when intangible factors affect a good's value (van der Rest, Roper and Wang, 2018). In real estate research, the hedonic pricing model seems to have the most application. The hedonic pricing model is founded on the basis that real estate values are affected by individual intrinsic and extrinsic factors (D'Acci, 2014). Intrinsic factors are factors that are strictly connected to the residence and include the size of the property, the quality of finishing, safety measures and other mainly tangible properties associated with the good. Extrinsic factors include all the factors that are related to the area in which the residence is located and include the quality of roads, the abundance of green space, public transport facilities, the number of shops, pollution and other properties associated with the area (D'Acci, 2014).

The hedonic pricing model is a strong estimator of real estate values (Lisi, 2019). By establishing the value of the extrinsic factors, the model allows buyers to not only price the house for its utility but also its livability factors. A buyer might desire a property that is small but in a quiet neighborhood, especially if that buyer intends to raise a family within that property. The difference in value due to extrinsic values could be rather high while houses are largely similar in size and fixtures.

The current research benefits from the hedonic pricing model because extrinsic variables, such as Airbnb activity and subjective livability could have an effect on residential real estate values. A buyer's willingness to pay for a house at a certain price is determined by factors within the hedonic pricing model defined by Rosen. Therefore, the market price for any house is consistent with the equilibrium between what buyers are willing to pay and what sellers are willing to accept, otherwise comparable to regular effects of demand and supply. That stated, the current analysis remains cognizant that the hedonic pricing model, as noted by Gibbs et al. (2017) and Furuta et al. (2021), is subjective to inefficiencies due to multicollinearity, such as due to the mismatch between the number of bedrooms and the number of bathrooms, spatial autocorrelation due to the effect of what houses in the neighborhood have recently sold for and sample selection bias where the pricing is affected by the pattern of sold houses while ignoring the effect of unsold houses in a neighborhood and what they might currently be valued at. The current research also recognizes the possibility of endogeneity, especially endogeneity due to reverse causality.

Fixed effects

The analysis used a fixed effects approach rather than a random effects approach for all regression steps of the mediation model. Fixed effects models are close to simple linear regression models (De Chaisemartin and D'Haultfœuille, 2020). The model assumes that the independent variable has a fixed relationship with the dependent variable across all observations (Plümper and Troeger, 2018). In this paper, time fixed effects were used to control for variables that vary over time. When looking at the dependent variable, residential real estate values, the analysis period spans from 2016 to 2020. The analysis period for subjective livability spans from 2015 to 2019. Using a time fixed effects approach effectively protected the analysis from the complexities of tracking and accounting for changing residential real estate values and livability scores over the research period. Using time fixed effects to control for price effectively offered data that was close enough to the actual pricing within the study period without creating computational confusion due to the market's movement over the same period. The same could be said about changing livability scores.

Location fixed effects are also worth considering. However, due to privacy reasons, livability data was only available at the neighborhood-level. Therefore, the rest of the data has been transformed from individual-level data into neighborhood-level data, so that all data was measured on the same level of aggregation. Unfortunately, this makes it impossible to add location fixed effects to the current research.

The regression steps of the mediation model for the current research are all functionally identical, which makes the use of a fixed effects model highly suitable. Importantly, the fixed effects model allowed to control for all time-variant omitted variables. Furthermore, the effects of omitted factors that are unaffected by time such as the size of the property or the number of shops were all controlled for easily. The time fixed effects helped to avoid the problem of treating and accounting for variables that are hard to observe and which were not included as control variables in this research.

However, a fixed effects approach presents several challenges and disadvantages, which should not go unaddressed. Among the most significant disadvantages is the need to estimate a number of additional parameters that might be relevant in an analysis (Brysbaert and Stevens, 2018). By adding fixed effects to a model, there exists a risk of ignoring factors that change variables over time. For example, it is possible that the shift from offices to remote working arrangements due to the pandemic changed how people value residential real estate in the Netherlands. A researcher cognizant of such a change could introduce a dummy variable to account for that change. However, the introduction of dummy variables increases noise levels for any analysis (Kirasich, Smith and Sadler, 2018). Increased noise levels could lead to inaccurate findings thereby sabotaging the entire research effort.

The mediation model

To evaluate the relationships between Airbnb activity, subjective livability and residential real estate values in the Netherlands, regression analysis was applied as the primary evaluative technique. Regression analysis provides a justifiable basis for explaining observed phenomena and predicting probable cause within the limitations of a research subjective matter (Ahlgren and Walberg, 2017; Brook and Arnold, 2018).

Informed by four constituent hypotheses, the study sought to address the research question through a modular approach. The mediation model proposed by Baron and Kenny (1986) was applied in the current research. The method proposed by Baron and Kenny (1986) consists of four steps in order to explain if there exists mediation in a given model and to what extent the effect is mediated through the mediator. To get a better understanding of the mediation model, the four steps of the mediation model are set out below.

Step 1: Conduct simple regression analysis where X predicts Y. The effect of X on Y is referred to as *c*. This step allows for the quantification of the effect of X on Y without taking into account the effect of a possible mediator. If the results from this regression are statistically significant, there exists an effect which could possibly be mediated by another variable. In the current research, various control variables are taken into account. The regression equation for step 1:

$$\ln \mathrm{P}_{it} = \beta_0 + \beta_1 \ln \mathrm{A}_{it-1} + \beta' \, \mathrm{N}_{it} + \beta' \, \mathrm{X}_{it} + \mathrm{TQ}_i + \varepsilon_{it} \tag{1}$$

Where P_{it} is the average transaction price of residential properties in neighborhood *i* in year *t.* A_{it-1} is the Airbnb activity in neighborhood *i* in year *t-1*. Every neighborhood consists of a mix of different properties, which could have an effect on the average transaction price. Therefore, a vector of intrinsic property characteristics, N_{it}, are included as a control variable, including the size of the property, the building period and the maintenance level. Likewise, the neighborhood itself could have an effect on the average transaction price. Therefore, a vector of extrinsic property characteristics, X_{it}, are included as control variables, including the percentage of non-western residents, the education level, the unemployment rate and the percentage of households with children. TQ_i then represents the quarterly time fixed effects and ε_{it} is the error term. β_0 is a constant, β_1 captures the effect of Airbnb activity and β' captures the effect of the various intrinsic and extrinsic property characteristics.

Step 2: Conduct simple regression analysis where X predicts M. The effect of X on M is referred to as *a*. This step allows for the quantification of the effect of X on M. If the results from this regression are statistically significant, there is evidence of a relationship between the independent variable and the mediator variable. In the current research, various control variables are taken into account. The regression equation for step 2:

$$\Lambda_{it} = \beta_0 + \beta_1 \ln \mathrm{A}_{it} + \beta' \, \mathrm{Z}_{it} + \mathrm{TY}_i + \varepsilon_{it} \tag{2}$$

Where Λ_{it} is the subjective livability score of neighborhood *i* in year *t.* A_{it} is the Airbnb activity in neighborhood *i* in year *t.* The subjective livability score might also be influenced by other neighborhood characteristics. Therefore, a vector of neighborhood characteristics, Z_{it}, are included as control variables, including the percentage of non-western residents, household composition, education level, duration of residence, a physical environment score and the number of services. TY_i then represents the yearly time fixed effects and ε_{it} is the error term. β_0 is a constant, β_1 captures the effect of Airbnb activity and β' captures the effect of the various control variables.

Step 3: Conduct simple regression analysis where M predicts Y. The effect of M on Y is referred to as *b*. This step allows for the quantification of the effect of M on Y. If the results from this regression are statistically significant, there is evidence of a relationship between the mediator variable and the dependent variable. In the current research, various control variables are taken into account. The regression equation for step 3:

$$\ln \mathrm{P}_{it} = \beta_0 + \beta_1 \Lambda_{it-1} + \beta' \, \mathrm{N}_{it} + \beta' \, \mathrm{X}_{it} + \mathrm{TQ}_i + \varepsilon_{it} \tag{3}$$

Where P_{it} is the average transaction price of residential properties in neighborhood *i* in year *t.* Λ_{it-1} is the subjective livability score of neighborhood *i* in year *t-1*. β_1 captures the effect of subjective livability. All other symbols have been discussed under step 1.

Step 4: Conduct multiple regression analysis where X and M predict Y. The effect of X on Y is referred to as *c'.* This step allows for the quantification of the effect of X and M on Y. If β_1 in the below regression equation is zero, the mediator completely mediates the relationship between X and Y. In the current research, various control variables are taken into account. The regression equation for step 4:

$$\ln \mathrm{P}_{it} = \beta_0 + \beta_1 \ln \mathrm{A}_{it-1} + \beta_2 \Lambda_{it-1} + \beta' \mathrm{N}_{it} + \beta' \mathrm{X}_{it} + \mathrm{TQ}_i + \varepsilon_{it} \tag{4}$$

Where P_{it} is the average transaction price of residential properties in neighborhood *i* in year *t.* A_{it-1} is the Airbnb activity in neighborhood *i* in year *t-1*. Λ_{it-1} is the subjective livability score of neighborhood *i* in year *t-1*. β_1 captures the effect of Airbnb activity and β_2 captures the effect of subjective livability. All other symbols have been discussed under step 1.

The mediation model posits the possibility that M mediates the effect of X on Y in such a way that the indirect effect of X on Y through M is opposite in sign to the direct effect of X on Y. It then follows that the research hypothesis is that the indirect effect of Airbnb activity on residential real estate values through subjective liveability dampens the direct effect of Airbnb activity on residential real estate values. This is also known as inconsistent mediation (MacKinnon, Fairchild and Fritz, 2007).

To calculate the indirect effect, the product of coefficients method is used. To calculate the direct effect and make some additional computations the causal steps approach proposed by Baron and Kenny (1986) is used. The product of coefficients method features fewer regression steps than the comparative causal steps approach, but it does not provide all the necessary data to analyze the mediation. That stated, the coefficients of path a and b was used to arrive at the indirect effect. The formula to calculate the indirect effect is as follows:

$$a * b \tag{5}$$

Where a is the effect of Airbnb activity on subjective livability and b is the effect of subjective livability on residential real estate values.

Furthermore, it is important to know if the indirect effect has any economic significance. To calculate if the indirect effect is economically significant, this paper will calculate what percentage of the total effect can be assigned as going through path $a * b$. This can be done with the following formula:

$$a * b \; / \; c \tag{6}$$

Where a is the effect of Airbnb activity on subjective livability, b is the effect of subjective livability on residential real estate values and c is the effect of Airbnb activity on residential real estate values without taking into account subjective livability as a mediator.

To test whether the indirect effect is statistically significant, the Sobel test is used. This test was first introduced by Sobel (1982) and provides an estimate of the statistical significance of the indirect effect. The ratio will then have to be treated as a Z-test. The formula to calculate the statistical significance of the indirect effect is as follows:

$$\frac{ab}{\sqrt{b^2 s_a^2 + a^2 s_b^2}} \tag{7}$$

Where a is the effect of Airbnb activity on subjective livability, b is the effect of subjective livability on residential real estate values, s_a is the standard error of a and s_b is the standard error of b.

Assumptions associated with general linear models were assumed to hold. It was assumed that there was inherent linearity in the data. It was also assumed that all the data used was distributed normally. Another assumption was the independence of errors such that residuals and the variables were assumed to have no association. The final assumption associated with linear models was the homogeneity of the error variance where the variances of two or more samples are assumed to be the same (Brooks and Tsolacos, 2010).

In addition to assumptions associated with linear models, three specification error assumptions associated with the mediation model were also considered relevant in the current research. It was assumed that reverse causal effects between the X and Y, and between X and M could exist. In the current context, reverse causal effects could exist between Airbnb activity and residential real estate values, and between Airbnb activity and subjective livability (Smith, 1982). To reduce the possibility of reverse causality between Airbnb activity and residential real estate values, the data on Airbnb activity is lagged with one year compared to the data on residential real estate values. Furthermore, an instrumental variables approach is taken to mitigate possible reverse causality in mediation steps *1, 2* and *4*. The second assumption was that there could exists no measurement error in the mediator. A measurement error in the mediator variable can cause biased direct and indirect effect estimates (Savalei, 2019). In the current context, the mediator is the variable subjective livability. Therefore, the assumption was that the variable subjective livability was measured accurately, otherwise, the analysis would have to include a corrective measure such as the application of an instrumental variable estimation to correct the measurement error (Ullah, Zaefarian and Ullah, 2021). The third assumption under the mediation model was that there were no omitted variables.

DATA

This section describes the data used for this research. The data came from three main sources. The first dataset contained information on Airbnb activity, the second dataset contained data on the subjective livability measure and the third dataset contained data on residential real estate.

Airbnb

Airbnb is a company that does not easily provide anonymized data on its users. Therefore, the data on Airbnb used in this paper was web-scraped from the Airbnb website. The web-scraped data on Airbnb has been provided by Dr. Cox of InsideAirbnb. Web-scraping is a technique that uses scripts written in a programming language such as Python to read publicly available data and export it to a datafile (Krotov and Tennyson, 2018). Web-scraping is used to collect digital data available at the HTML-level of the website. This is different from screen scraping which refers to collecting data that is displayed by the website (Han and Anderson, 2020). As a data collection technique, web-scraping can be powerful for collecting data that is not immediately apparent to a website's visitor. The technique uses bots and crawlers to read through a website's HTML-code and copy data of the desired type (Han and Anderson, 2020). Web-scraping also has the benefit of allowing a researcher full control over the collection pipeline of vast unstructured primary data (Gyódi, 2019).

The web-scraping dataset used in this paper started in April 2015. Most of the data for the first three months of the year 2015 was scraped and stored. Following the initial web-scraping in April 2015, there were subsequent data collection efforts through the same technique between the April 2015 and January 2020. Data was scraped from the Airbnb website several times a year. The individual web-scraped datasets were then combined to form one dataset which would include all listings and reviews from January 2015 to December 2019. This has been done because the data collected at the end of the research period would not be fully representative of all listings and reviews over the entire research period. Due to the fact that Airbnb regularly deletes inactive listings and their corresponding reviews as part of the platform's internal quality control, listings and reviews further in the past had a higher chance of being deleted than recently booked listings and their corresponding reviews (Xie and Mao, 2017; Crommelin et al., 2018). Unfortunately, this would also lead to the fact that there is no way to tell whether the data scraped for the first three months of the year 2015 contained all the listings and reviews of that period.

The location data for the listings included in the dataset was anonymized by Airbnb. Anonymization of data is an ethical research technique useful to protect the privacy of individuals using the Airbnb platform (Krotov and Tennyson, 2018). Airbnb facilitated the anonymization of location data through its internal search parameters. By allowing a location error of approximately 150 meters, the website prevented unnecessary revelation of actual addresses for listings. As such, Airbnb's location anonymization leads to the fact that apartments in the same building might be displayed as being scattered within the 150-meter location radius.

The Airbnb data was divided in two different datasets: A listings dataset and a reviews dataset. The Airbnb listings dataset contained listing IDs, listing type and the World Geodetic System (WGS) latitude and longitude. The Airbnb reviews dataset contained the listing IDs and the date of every review for that particular listing. The listings data and reviews data could be matched through the listing IDs, so that every review had information about the listing type and location. As the other datasets contained location data in the RD coordinate system, the Airbnb location data has been transformed from the WGS coordinate system to the RD coordinate system through the online coordinate reprojection tool of LocusFocus (2020). To map the listing and reviews and assign them to the corresponding neighborhood, ArcGIS was used. With the use of polygons of the neighborhoods of the municipality of Amsterdam, it was possible to assign the listings and reviews to a certain neighborhood.

Airbnb activity was proxied by the number of reviews rather than the number of listings. This paper considered both options and concluded that, theoretically, reviews carried more weight. The variance in a listings' booking could be high with some listings having less than ten bookings per year, while other listings would have than 200 annual bookings. Listings with more bookings per year could add more stress to the livability of the neighborhood. Therefore, it would be more rational to assign more weight to the highly booked listing. However, the number of listings is still of importance in this research as they are being used to check the robustness of the results.

This paper sought to establish how short-term rental market dynamics affect residential real estate values and the livability of a neighborhood. While Airbnb is not the only platform offering home-sharing in Amsterdam, the company has the biggest market share; data from Airbnb, therefore, was a reliable estimator of the industry's presence in the city. Additionally, Airbnb hosts in Amsterdam have the freedom to list their homes on other platforms active in the city. Including listings from other platforms presented a risk of double counting the same properties (Garcia-Lopez et al., 2020). The risk presented by spam reviews has also been considered. While guests are only able to post a review once after they have stayed at a certain host's property and Airbnb has multiple measures to detect spam reviews (Airbnb, 2020c), it can be concluded that spam reviews were not significant enough to bias the statistical robustness of all reviews.

After the collection of Airbnb data in Amsterdam, 51,131 listings were obtained. While this study is only interested in listings with a review in the years 2015, 2017 or 2019, 13,934 listings which did not have a review in the years 2015, 2017 or 2019 were deleted. Furthermore, it is important to assign the listing to a certain neighborhood. Therefore, 182 listings which could not be assigned to a neighborhood were deleted. A further 197 listings with missing data were deleted. After the data cleaning process, 36, 818 listings remained.

The initial number of reviews collected was 948,072. While this study is only interested in reviews from the years 2015, 2017 and 2019, 441, 262 reviews with a date other than 2015, 2017 and 2019 were deleted. Another 5,267 reviews with missing data were deleted. The total number of reviews remaining after cleaning the data was 501,543. Data with listing type "shared room" was excluded from the regression analysis because there were not enough listings to warrant the inclusion of the shared rooms.

Table 1
Descriptive statistics Airbnb listings

	No. Listings					
	2015		**2017**		**2019**	
	Abs.	**%**	**Abs.**	**%**	**Abs.**	**%**
Entire home	10612	80,4%	16454	80,4%	12650	77,6%
Private room	2498	18,9%	3940	19,2%	3599	22,1%
Shared room	86	0,7%	80	0,4%	62	0,4%
Total	13196		20474		16311	
	Host type					
	2015		**2017**		**2019**	
	Abs.	**%**	**Abs.**	**%**	**Abs.**	**%**
Hosts with 1 listing	9661	89,6%	14717	88,1%	11593	85,9%
Hosts with multiple listings	1125	10,4%	1986	11,9%	1904	14,1%
Total	10786		16703		13497	
	No. Listings per host					
	2015		**2017**		**2019**	
	Abs.	**%**	**Abs.**	**%**	**Abs.**	**%**
Listings (host has 1 listing)	10056	76,2%	15787	77,1%	12423	76,2%
Listings (host has multiple listings)	3140	23,8%	4687	22,9%	3888	23,8%
Total	13196		20474		16311	

Table 1 shows the descriptive statistics for Airbnb listings. Between 2015 and 2017, the number of Airbnb listings increased. However, between 2017 and 2019 the number of listings declined. Noticeable is the fact that there is a shift between entire home listings to private room listings from 2017 to 2019. This could be due to new regulations regarding the rental of entire homes. That stated, the percentage of hosts with multiple listings rose steadily from 2015 to 2019. Although the total number of listings declined from 2017 to 2019, it can be concluded that less professional hosts with multiple listings stopped renting on Airbnb compared to hosts with one listing. However, it can be concluded that not more listings are in the hands of professional hosts compared to hosts with one listing. Between 2015 and 2019, the percentage of listings where the host has one listing stayed approximately the same.

Table 2
Descriptive statistics Airbnb reviews and prices

No. reviews

	2015 Abs.	2015 %	2017 Abs.	2017 %	2019 Abs.	2019 %
Entire home	100198	73,1%	130259	65,7%	86767	52,2%
Private room	35988	26,3%	67185	33,9%	77869	46,9%
Shared room	841	0,6%	867	0,4%	1569	0,9%
Total	137027		198311		166205	

No. reviews per listing

	2015				2017				2019			
	Mean	Median	Min.	Max.	Mean	Median	Min.	Max.	Mean	Median	Min.	Max.
Entire home	9,4	5	1	122	7,9	5	1	386	6,9	7	1	201
Private room	14,4	7	1	129	17,1	9	1	148	21,6	37,5	1	395
Shared room	9,8	6	1	61	10,8	5,5	1	95	25,3	12	1	218
Total	10,4	5	1	129	9,7	6	1	386	10,2	7	1	395

Prices

	2015				2017				2019			
	Mean	Median	Min.	Max.	Mean	Median	Min.	Max.	Mean	Median	Min.	Max.
Entire home	137	120	18	1400	145	125	8	2100	164	140	5	1400
Private room	76	70	10	549	84	75	15	952	102	85	10	1285
Shared room	51	45	19	180	71	53	13	345	71	60	15	1000
Total	125	109	10	1400	133	115	8	2100	150	125	5	1400

Table 2 shows the descriptive statistics for Airbnb reviews and prices. For Airbnb reviews, the analysis suggested that, the total number of reviews increased from 2015 to 2017, but decreased from 2017 to 2019. Interesting to note is that, over the research period, private rooms were becoming more popular than entire homes. This could be the result of legislation on renting entire homes or a cultural shift by people who were looking to book an Airbnb. In each year of the research period, private rooms had, on average, more reviews per listing than entire homes. This suggests that private rooms are more popular than entire homes in Amsterdam. Furthermore, it can be seen that the number of reviews per entire home listing is decreasing between 2015 and 2019, while the number of reviews per private room listing is increasing between 2015 and 2019. Again, this could be due to a change in market preference or in response to legislation prohibitive of the rental of entire homes. Figure 2 shows a map of the municipality of Amsterdam with the corresponding the number of reviews per neighborhood in 2019, the most recent year of the analysis period. A map for the years 2015 and 2017 can be found in appendix I.

The analysis also reviewed that the prices for booking an Airbnb, be it a private room or the entire home, were gradually rising over time. This could be due to the interplay between demand and supply, or it could reflect the economy's performance especially concerning inflation.

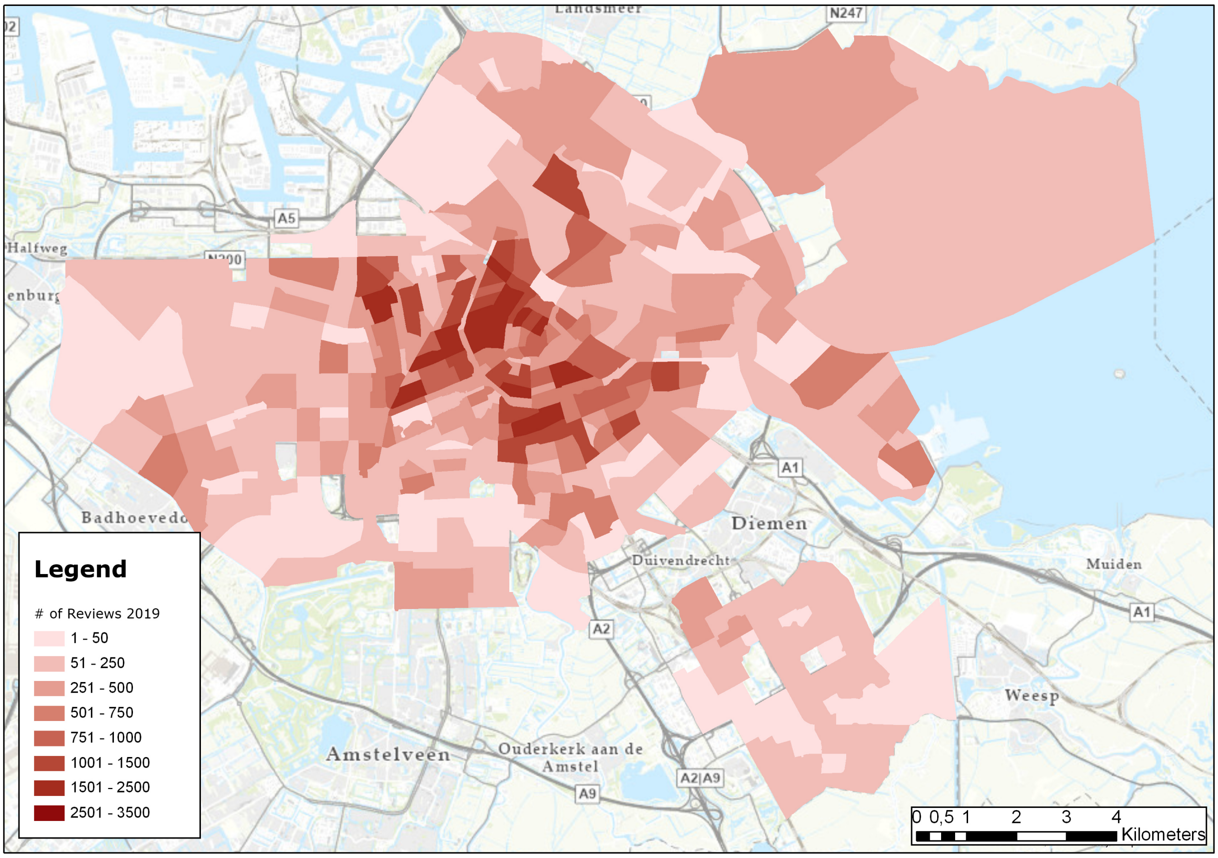

Figure 2: *The number of reviews per neighborhood of the municipality of Amsterdam in 2019*

Subjective livability

Subjective livability is not an easily accessible concept, especially for people who do not hold a degree in social sciences (Okulicz-Kozaryn and Valente, 2019). Considering that this research strived to include a subjective measure of livability which would come directly from the people involved, the concept of subjective livability had to be proxied with a question that was not only more intuitive but also less fatiguing for the target population. The question posed to the respondents was, "How satisfied are you with your neighborhood? (Total score)". While the question does not capture the full scope of the concept of subjective livability, it was close enough to capture the concept within this research's context.

The data on subjective livability was obtained from the Municipality of Amsterdam. A survey called "Wonen in Amsterdam" (Living in Amsterdam) facilitated the data collection once every two years. The dataset includes data for the years 2015, 2017 and 2019. In total, there are 481 neighborhoods in Amsterdam. Data was collected for three years, which means there were 1443 observations on record. However, some neighborhoods did not provide the data necessary for this research. Consequently, some neighborhoods had to be dropped for the subjective livability dataset. Eventually, the subjective livability dataset contained 812 observations.

The control variables for subjective livability included the percentage of non-western residents, the composition of households, the level of education in percentages, the duration of residence, a rating concerning the physical environment and the number of services available in the neighborhood. The control variables were carefully selected to avoid correlation with Airbnb activity.

As noted by Boterman, Musterd and Manting (2020), the composition of a household is considered an indicator to the strain on social infrastructure in the area. The composition of households could therefore be an indicator of subjective livability. Households can be divided over five categories based on composition. The categories were one-person households, including persons living in a room, such as students; one-parent households with one or more children; households with more than one adult but without children; households with more than one adult and with children; and other household compositions (those not in another category). The data on the composition of households has been obtained from the department of Research, Information and Statistics (OIS) of the Municipality of Amsterdam.

Houses in areas that have a high duration of residence are considered desirable and therefore of higher value than houses with a lower duration of residence (Needham, Kruijt and Koenders, 2018). In this research, the duration of residence referred to the average number of years a resident has lived in the same house since the last move. Data on the duration of residence has been provided by the IOS department of the municipality of Amsterdam.

According to D'Acci (2014), the physical characteristics of a place, such as the proximity to green spaces and a pleasant view, have an effect on livability. The physical environment consists of many factors. This research therefore uses the physical environment rating of the Leefbaarometer. The Leefbaarometer is a composite indicator of livability which has been developed by researchers for the Dutch government. The physical environment rating of the Leefbaarometer consists of 29 individual physical environment characteristics. The data on the physical environment rating has been obtained from the Dutch Ministry of Internal Affairs and Kingdom Relations (Ministry of Internal Affairs and Kingdom Relations, 2016).

Livability is also subjective to available services, considering that areas with access to desirable services are considered more prime than areas without the same level of access to services (Janssen, Daamen and Verdaas, 2021). For this study, the services considered include educational services, the police, the fire department, cultural and sports services, recreational services, healthcare services and social care services. Data on the availability of services for neighborhoods was obtained from Amsterdam's registry of companies (Bedrijvenregister Amsterdam (ARRA)).

The percentage of non-western residents is an important factor for subjective livability. A multiethnic neighborhood could have residents with opposing norms and values. Opposing norms and values could decrease residents' subjective livability (Dekker and Bolt, 2005; Leby and Hashim, 2010). For this research, a non-western resident is defined as a person which has been born in a non-western country or with one or both parents being born in a non-western country. The data on non-western residents has been obtained from the OIS department of the Municipality of Amsterdam.

Typically, a neighborhood where people are generally highly educated is considered more desirable (Okulicz-Kozaryn and Valente, 2019). The measure of the level of education used in this research relates to the education level of all residents aged between 15 and 74 years old and comprises three categories, namely low, mid and high. The category 'low' is comprised of residents with a vmbo-diploma or lower. The 'mid' category includes all residents with an mbo-, havo- or vwo-diploma. The 'high' category is comprised of residents who hold a hbo or university degree. Data on the level of education for residents was obtained from the Dutch Central Bureau of Statistics (CBS).

Residential real estate values

The data on residential real estate has been provided by the Dutch Association of Real Estate Agents (NVM). To mitigate the possibility of endogeneity, all data other than the residential real estate data has been lagged by one year, leading to the use of residential real estate data from the years 2016, 2018 and 2020. For every transaction the NVM dataset includes the date of transaction, the transaction price, the postcode, the house number, the size of the property in square meters, the building period and multiple other intrinsic characteristics of the property. For this research, it was important to determine the location of each property and to assign the property to a certain neighborhood. To determine the exact location of the property, the postcode and house number were used to find the full address. The full address was then used to find the WGS coordinates through the use of the Excel Geocoding add-in from Adventures in CRE (Burton, 2020). The Excel add-in cleverly integrates Google's Geocoding API in Excel, which makes it possible to find the WGS coordinates. Finally, the WGS coordinates were converted to RD coordinates through the use of the online coordinate reprojection tool of LocusFocus (2020).

Originally, the NVM dataset contained 84,140 observations for transactions that took place in the municipality of Amsterdam from 2011 to 2020. This research is only interested in transactions that took place in the years 2016, 2018 and 2020. Therefore, 58,132 observations that took place in a year other than 2016, 2018 or 2020 were deleted. Observations concerning transactions on other real estate than purely residential, such as mixed-use developments or parking facilities were also deleted, further reducing the observations by 211. Any transactions with missing data were removed, as were transactions that could not be assigned to a certain neighborhood, deleting 227 observations. After cleaning the data, the residential real estate dataset comprised 25,570 observations.

The control variables for residential real estate values can be divided into two categories, namely intrinsic characteristics and extrinsic characteristics. All control variables were carefully selected to avoid correlation with Airbnb activity.

Intrinsic characteristics

The intrinsic characteristics of properties sold were obtained from the NVM dataset. The specific characteristics used in this research were the property's surface area in square meters, the state of inside maintenance and the building period.

To manipulate the surface area for subsequent data analysis, the surface area in square meters was transformed into a natural log.

The inside maintenance of properties was evaluated using three main categories. The selling real estate agent would assign the property a rating of between 1 and 10, with 1 being the worst score and 10 being the best score. The scores were then categorized into three categories, namely good, moderate and bad. Properties with a rating between 1 and 5 are categorized as bad, properties with a rating of 6 or 7 are categorized as moderate and properties with a rating of 8 or higher are categorized as good. By categorizing the maintenance rating, the number of variables is reduced significantly, which positively affects the robustness of the results.

The NVM dataset contains the building period of the properties and consist of nine categories. To reduce the number of variables, the building period categories are reduced to five categories, namely 1500-1905, 1906-1944, 1945-1970, 1971-1990, 1991-2020. The reduction of the number of categories positively affects the robustness of the results.

Extrinsic characteristics

The extrinsic characteristics of the properties used in this research were obtained from multiple governmental agencies. The specific characteristics used were the percentage of non-western residents, the level of education in percentages, the unemployment rate and the percentage of households with children.

The percentage of non-western residents is an important factor for residential real estate values. Van der Greft, Musterd and Thissen (2014) noted that the percentage of non-western residents can affect perceived residential real estate values in Amsterdam. The data on non-western residents has been obtained from the OIS department of the Municipality of Amsterdam.

Typically, a neighborhood where people are generally highly educated is considered more desirable and generally affects real estate prices positively (Okulicz-Kozaryn and Valente, 2019). Data on the level of education for residents was obtained from the Dutch CBS.

According to Liu and Clark (2016) people that own relatively more expensive houses are predicted to have more children. This research therefore considers that children could be of importance to residential real estate values. Data on the percentage of households with children has been obtained from the OIS department of the Municipality of Amsterdam.

Reichert (1990) finds that the unemployment rate has a negative effect on residential real estate values. This paper therefore includes the unemployment rate as a control variable for residential real estate values. The measure used in this paper considers the percentage of residents between 15 and 65 years old that are unemployed when they are officially registered as unemployed. The data on unemployment is provided by the Dutch CBS and the Department Work and Income (DWI) of the municipality of Amsterdam.

The NVM statistics showed that transaction prices were increasing over the years. The analysis also showed that the amount of residential real estate sold was decreasing from 2016 to 2018, but increased slightly from 2018 to 2020. The surface area of the units sold was found to be rising through the years. The NVM descriptive statistics can be found in appendix A.

This research aggregates all data on the neighborhood-level. Therefore, it is important to look at the neighborhood-level data. As can be seen in table 3, the mean transaction price per neighborhood is €503,591. On average, 30% of the buildings in a neighborhood were built between 1906 and 1944. Likewise, 74% of the buildings in a neighborhood are considered moderately maintained.

Table 3
Descriptive statistics neighborhood-level

	Mean	Median	Std. Dev.	Min.	Max.	25th percentile	75th percentile
Transaction price	503591	446845	249938	153949	1873098	336817	591312
Surface area in m^2	94,17	89,05	28,08	38,50	296,00	73,85	108,05
Building period (%)							
1500-1905	17,36		28,44	0	100		
1906-1944	30,39		38,04	0	100		
1945-1970	12,91		26,89	0	100		
1971-1990	13,57		27,28	0	100		
1991-2020	25,76		35,48	0	100		
Maintenance (%)							
Good	19,03	17,24	14,81	0	100	8,57	26,67
Moderate	74,39	7,55	15,81	0	100	66,67	84,62
Bad	6,58	4,06	9,47	0	100	0	10
Transaction date category (%)							
2016-01	6,9		12,07	0	75		
2016-02	8,6		14,25	0	66,67		
2016-03	7,11		12,31	0	100		
2016-04	7,56		13,07	0	100		
2018-01	7,62		13,62	0	100		
2018-02	9,13		15,04	0	100		
2018-03	8,25		13,4	0	66,67		
2018-04	9,48		15,43	0	100		
2020-01	6,06		10,33	0	80		
2020-02	9,48		15,18	0	100		
2020-03	9,62		14,91	0	100		
2020-04	10,19		15,76	0	100		
Reviews							
All	495	345	466	14	2.331	165	665
Apartments	313	196	338	1	1.849	72	429
Private rooms	179	127	179	1	1.317	53	239
Listings							
All	50	36	46	2	265	16	69
Apartments	40	28	40	1	223	11	56
Private rooms	10	8	8	1	51	4	14
Subjective liveability	7,59	7,70	0,65	5,90	8,80	7,20	8,10
Non-western (%)	30,18		18,39	3,90	81,60		
Education (%)							
High	48,18	52,00	17,11	10,00	83,17	35,00	62,00
Mid	30,19	29,00	7,50	8,47	58,33	25,00	35,00
Low	21,61	19,92	11,75	0,87	69,49	11,86	29,00
Unemployment (%)	10,91		4,83	1,40	31,00		
Households (%)							
With children	25,34		11,28	1,80	69,60		
One adult	51,82		11,29	16,10	85,10		
One adult with child(ren)	8,59		4,08	0,40	31,00		
More than one adult without child(ren)	21,48		4,47	8,30	44,40		
More than one adult with child(ren)	16,75		9,04	1,40	55,50		
Duration of residence (years)	8,83	8,90	2,31	0,50	15,90	7,70	10,00
Physical environment rating	-0,16	-0,12	0,13	-0,55	0,08	-0,27	-0,06
Number of services	79,42	69,00	45,25	4,00	281,00	45,00	106,00
Number of cultural establishments	37,49	29,00	28,39	0,00	165,00	16,00	54,00
Number of horeca establishments	13,92	9,00	15,94	0,00	125,00	5,00	17,00
Number of observations	788						

On average, there are 50 Airbnb listings per neighborhood. Distinguishing between entire home and private room listings, there are on average 40 entire home listings and 10 private rooms listings per neighborhood. When analyzing the number of reviews, on average, 495 reviews have been written per neighborhood. Distinguishing between entire home and private room reviews, there are on average 313 entire home reviews and 179 private room reviews per neighborhood. Interesting to note is the relatively high standard deviations for all the above means. This suggests that there are neighborhoods with lots of listings and reviews and neighborhoods with only a few listings and reviews.

The analysis showed that the average subjective livability score is relatively high, while the standard deviation is comparatively low. This means that residents of Amsterdam are quite happy about their neighborhood, but do not rate their neighborhood as either very bad or very good.

It can be seen that, on average, Amsterdam is highly educated, with more than 48% of residents having a hbo or university degree. That could be the result of the city having two major universities and multiple other institutions of higher education. Furthermore, it is interesting to note that more than half of all household are one-adult household. Again, this could be due to the fact that Amsterdam has a high number of students. As has been clarified in the data section, students are considered a one-adult household.

Time fixed effects

This research uses time fixed effects to control for time-variant omitted variables. To add time fixed effects, dummies were created. For all regressions where the residential real estate value is the dependent variable, this was possible because every observation included the date of the transaction. Consequently, it was possible to divide the observations into categories, each consisting of the observations that happened in a certain quarter.

For the regression where subjective livability is the dependent variable, the year of the subjective livability score was known. It was therefore possible to divide the observations into categories, each consisting of the observations that happened in a certain year.

Instrumental variables

To mitigate the possibility of endogeneity of the variable Airbnb activity, an instrumental variables approach is taken. The two instrumental variables of interest were the number of cultural establishments and the number of horeca (hotels, restaurants and cafes) establishments. The relationship between Airbnb activity and cultural establishments in Amsterdam is partially defined by the attractiveness of cultural establishments to Airbnb visitors. Areas with a rich cultural profile can offer visitors more because visitors can experience immersive experiences while staying close to their accommodation (Abusedou and Zakaria, 2020). Airbnbs should therefore be concentrated to areas which have more cultural establishments.

The same can be said on the association between Airbnb activity and horeca establishments. Guttentag (2019) considers the Airbnb a product of convenience. With such a product, the customer is looking to maximize their value for money. Areas with horeca establishments provide convenience for visitors and present an opportunity to maximize value through a variety of dining and entertainment options in proximity to the accommodation.

Other

The data used for the analysis needed to be as close to a normal distribution as possible. Using normally distributed data is preferred because research has observed that many natural phenomena are normally distributed (Frank, 2009). A normally distributed dataset, therefore, is likely to provide the best chance for understanding a research phenomenon. Not all data collected was normally distributed. To create a degree of normal distribution, the data were converted using a uniform method; the use of natural logs. Since the actual data points are representative of a variable, conversion using natural logs did not impact the accuracy of representation. That is why datasets for residential real estate value, Airbnb reviews, the surface area of the properties in square meters, the number of services, the number of cultural establishments and the number of horeca establishments were all converted using the natural log.

The data analysis excluded outliers for the variables Airbnb activity, transaction price and subjective livability. For these three variables, the top 0.5 percent and the bottom 0.5 percent were excluded. For other variables, the data was left as is because the other variables were not as significant to the study as the three main variables forming the X, Y and M variables as defined in the mediation model.

RESULTS

In this section, the main results of this research are presented. The results section follows the regression regime outlined in the methodology section. First, a regression where Airbnb reviews predicts residential real estate values is performed. Second, a regression where Airbnb reviews predicts subjective livability is performed. Third, a regression where subjective livability predicts residential real estate values is performed. Fourth, a regression where Airbnb reviews and subjective livability predict residential real estate values is performed. Fifth, an IV regression is performed for some of the above-mentioned relationships. At last, the significance of the results will be calculated.

Airbnb activity predicting residential real estate values

To determine if there exists a relationship between two variables that could be mediated by another variable, a regression where Airbnb reviews predicts residential real estate values is performed. The regression results are shown in table 4.

Column (1) shows the basic regression with Airbnb reviews as the independent variable and residential real estate values as the dependent variable. The results suggest that Airbnb reviews have a positive effect on residential real estate values; on average, a 1 percent increase in Airbnb reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.163 percent increase of the average residential real estate value in that neighborhood. The estimate is significant at the 1 percent level. The associated adjusted R-squared, explaining how much of the variance in the dependent variable can be explained by the model, is only 17.3 percent.

The addition of the intrinsic property characteristics to the model leads to the results in column (2). By adding the intrinsic property characteristics, the effect of Airbnb reviews on residential real estate values decreased compared to the results of column (1). In this model, on average, a 1 percent increase in Airbnb reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.109 percent increase of the average residential real estate value in that neighborhood. The estimate is significant at the 1 percent level. The addition of the intrinsic property characteristics to the model raises the adjusted R-squared from 17.3 percent to 76.3 percent. This suggests that the intrinsic property characteristics helped to explain the variation in the dependent variable.

Table 4
Baseline regression results: the effect of all Airbnb reviews on residential real estate values

	(1) Basic	(2) Intrinsic property characteristics	(3) Extrinsic property characteristics	(4) Time fixed effects	(5) IV regression
Reviews - All (*ln*)	0.163***	0.109***	0.067***	0.038***	0.038***
	(0.016)	(0.011)	(0.009)	(0.008)	(0.009)
Surface area in m^2 (*ln*)		1.077***	1.027***	0.933***	0.937***
		(0.038)	(0.037)	(0.037)	(0.023)
Building period - 1500-1905		0.428***	0.179***	0.273***	0.273***
		(0.055)	(0.046)	(0.045)	(0.030)
Building period - 1906-1944		0.354***	0.183***	0.225***	0.223***
		(0.044)	(0.037)	(0.035)	(0.021)
Building period - 1945-1970		0.002	0.005	0.045	0.037*
		(0.057)	(0.038)	(0.038)	(0.022)
Building period - 1991-2020		0.044	0.027	0.074**	0.072***
		(0.052)	(0.036)	(0.034)	(0.021)
Maintenance - Good		0.407***	0.282***	0.412***	0.417***
		(0.117)	(0.068)	(0.057)	(0.053)
Maintenance - Moderate		0.125	0.132**	0.190***	0.188***
		(0.108)	(0.063)	(0.054)	(0.048)
Non-Western			-0.003***	-0.004***	-0.004***
			(0.001)	(0.001)	(0.000)
Education - Low			-0.344**	-0.557***	-0.542***
			(0.155)	(0.125)	(0.098)
Education - Mid			-1.060***	-0.848***	-0.821***
			(0.149)	(0.117)	(0.081)
Unemployment			0.004	0.010***	0.011***
			(0.003)	(0.002)	(0.002)
Households with children			-0.005***	-0.003***	-0.003***
			(0.001)	(0.001)	(0.001)
Constant	12.032***	7.197***	8.328***	8.422***	8.870***
	(0.094)	(0.226)	(0.204)	(0.205)	(0.153)
Intrinsic property characteristics	No	Yes	Yes	Yes	Yes
Extrinsic property characteristics	No	No	Yes	Yes	Yes
Time fixed effects	No	No	No	Yes	Yes
IV regression	No	No	No	No	Yes
Number of observations	812	812	788	788	765
Adjusted R-squared	0.173	0.763	0.843	0.917	0.915

Notes : The dependent variable is the natural logarithm of the neighbourhood-average residential real estate value. The number of Airbnb reviews is measured as the natural logarithm of the total number of Airbnb reviews of the year prior to the transaction year. IV regression: The number of Airbnb reviews is instrumented by the natural logarithm of the number of horeca establishments and the natural logarithm of the number of cultural establishments. All variables are measured at the neighbourhood-year level. The standard errors are clustered at the neighbourhood level. The standard errors are given between parentheses. The level of significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

Column (3) represents the addition of the extrinsic property characteristics to the model. By adding the extrinsic property characteristics, the effect of Airbnb reviews on residential real estate values decreased compared to the results of column (2). In this model, on average, a 1 percent increase in Airbnb reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.067 percent increase of the average residential real estate value in that neighborhood. The estimate is significant at the 1 percent level. The addition of the extrinsic property characteristics to the model raises the adjusted R-squared from 76.3 percent to 84.3 percent. This suggests that the extrinsic property characteristics helped to explain the variation in the dependent variable.

The addition of time fixed effects to the model leads to the results in column (4). By adding the time fixed effects, the effect of Airbnb reviews on residential real estate values decreased compared to the results of column (3). In this model, on average, a 1 percent increase in Airbnb reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.038 percent increase of the average residential real estate value in that neighborhood. The estimate is significant at the 1 percent level. The addition of the time fixed effects to the model raises the adjusted R-squared from 84.3 percent to 91.7 percent. This suggests that the time fixed effects helped to explain the variation in the dependent variable.

Airbnb activity predicting subjective livability

To determine if there exists a relationship between the independent variable and the mediator variable, a regression where Airbnb reviews predicts subjective livability is performed. The regression results are shown in table 5.

Table 5
Baseline regression results: the effect of all Airbnb reviews on subjective livability

	(6)	**(7)**	**(8)**	**(9)**
	Basic	**Neighborhood characteristics**	**Time fixed effects**	**IV regression**
Reviews - All (*ln*)	0.205***	-0.076***	-0.090***	-0.321***
	(0.021)	(0.020)	(0.020)	(0.045)
Non-Western		-0.021***	-0.021***	-0.024***
		(0.002)	(0.002)	(0.002)
Education - Low		-1.907***	-1.903***	-1.767***
		(0.230)	(0.232)	(0.250)
Education - Mid		-1.331***	-1.371***	-1.514***
		(0.224)	(0.229)	(0.253)
Household - One adult		0.073***	0.074***	0.048**
		(0.020)	(0.020)	(0.022)
Household - One adult with child(ren)		0.106***	0.106***	0.068***
		(0.020)	(0.020)	(0.023)
Household - More than one adult without child(ren)		0.067***	0.068***	0.035
		(0.021)	(0.021)	(0.024)
Household - More than one adult with child(ren)		0.078***	0.079***	0.051**
		(0.020)	(0.020)	(0.022)
Duration of residence (years)		0.039***	0.038***	0.032***
		(0.007)	(0.007)	(0.008)
Physical environment rating		-0.659***	-0.682***	-0.921***
		(0.121)	(0.122)	(0.136)
Number of services (*ln*)		0.124***	0.137***	0.343***
		(0.030)	(0.030)	(0.047)
Constant	6.410***	1.057	0.974	4.420*
	(0.120)	(1.999)	(1.995)	(2.273)
Neighborhood characteristics	No	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes
IV regression	No	No	No	Yes
Number of observations	812	800	800	777
Adjusted R-squared	0.108	0.710	0.712	0.670

Notes : The dependent variable is the subjective livability rating of the year prior to the transaction year. The number of Airbnb reviews is measured as the natural logarithm of the total number of Airbnb reviews of the year prior to the transaction year. IV regression: The number of Airbnb reviews is instrumented by the natural logarithm of the number of horeca establishments and the natural logarithm of the number of cultural establishments. All variables are measured at the neighbourhood-year level. The standard errors are given between parentheses. The level of significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

Column (6) shows the basic regression with Airbnb reviews as the independent variable and subjective livability as the dependent variable. The results suggest that Airbnb reviews have a positive effect on subjective livability; on average, a 1 percent increase in Airbnb reviews in a neighborhood results in a 0.00205 unit increase of the average subjective livability score of that neighborhood. The estimate is significant at the 1 percent level. The associated adjusted R-squared, explaining how much of the variance in the dependent variable can be explained by the model, is only 10.8 percent.

The addition of the neighborhood characteristics to the basic model of column (6) results in the effect of Airbnb reviews on subjective livability becoming negative. Column (7) represents the addition of the neighborhood characteristics. In this model, on average, a 1 percent increase in Airbnb reviews in a neighborhood results in a 0.00076 unit decrease of the average subjective livability score of that neighborhood. The estimate is significant at the 1 percent level. The addition of the neighborhood characteristics to the model raises the adjusted R-squared from 10.8 percent to 71 percent. This suggests that the neighborhood characteristics helped to explain the variation in the dependent variable.

Column (8) represents the addition of the time fixed effects to the model. By adding the time fixed effects, the effect of Airbnb reviews on subjective livability increased in magnitude compared to the results of column (7). In this model, on average, a 1 percent increase in Airbnb reviews in a neighborhood results in a 0.0009 unit decrease in the average subjective livability score of that neighborhood. The estimate is significant at the 1 percent level. The addition of the time fixed effects to the model raises the adjusted R-squared from 71 percent to 71.2 percent. This suggests that the time fixed effects had little effect in explaining the variation in the dependent variable.

Subjective livability predicting residential real estate values

To determine if there exists a relationship between the mediator variable and the dependent variable, a regression where subjective livability predicts residential real estate values is performed. The regression results are shown in table 6.

Column (10) shows the basic regression with subjective livability as the independent variable and residential real estate values as the dependent variable. The results suggest that subjective livability has a positive effect on residential real estate values; on average, a one-unit increase in the average subjective livability score of a neighborhood a year prior to the transaction year of the properties results in a 46.67 percent increase of the average residential real estate value in that neighborhood. The estimate is significant at the 1 percent level. The associated adjusted R-squared, explaining how much of the variance in the dependent variable can be explained by the model, is only 37 percent.

Column (11) represents the addition of the intrinsic property characteristics to the model. By adding the intrinsic property characteristics, the effect of subjective livability on residential real estate values decreased compared to the results of column (10). In this model, on average, a one-unit increase in the average subjective livability score of a neighborhood a year prior to the transaction year of the properties results in a 19.01 percent increase of the average residential real estate value in that neighborhood. The estimate is significant at the 1 percent level. The addition of the intrinsic property characteristics to the model raises the adjusted R-squared from 37 percent to 76.9 percent. This suggests that the intrinsic property characteristics helped to explain the variation in the dependent variable.

Table 6
Baseline regression results: the effect of subjective livability on residential real estate values

	(10)	**(11)**	**(12)**	**(13)**
	Basic	**Intrinsic property characteristics**	**Extrinsic property characteristics**	**Time fixed effects**
livability	0.383***	0.174***	0.074***	0.056***
	(0.023)	(0.015)	(0.020)	(0.018)
Surface area in m^2 (*ln*)		0.905***	0.992***	0.910***
		(0.036)	(0.037)	(0.037)
Building period - 1500-1905		0.570***	0.313***	0.350***
		(0.052)	(0.047)	(0.044)
Building period - 1906-1944		0.359***	0.233***	0.254***
		(0.044)	(0.038)	(0.035)
Building period - 1945-1970		0.072	0.027	0.059
		(0.055)	(0.041)	(0.040)
Building period - 1991-2020		0.114**	0.067*	0.098***
		(0.049)	(0.038)	(0.035)
Maintenance - Good		0.389***	0.263***	0.419***
		(0.093)	(0.065)	(0.053)
Maintenance - Moderate		0.145*	0.140**	0.207***
		(0.084)	(0.061)	(0.051)
Non-Western			-0.000	-0.003***
			(0.001)	(0.001)
Education - Low			-0.401**	-0.557***
			(0.157)	(0.129)
Education - Mid			-1.167***	-0.895***
			(0.141)	(0.112)
Unemployment			0.003	0.009***
			(0.003)	(0.002)
Household - With children			-0.006***	-0.004***
			(0.001)	(0.001)
Constant	10.064***	7.198***	8.272***	8.284***
	(0.175)	(0.192)	(0.265)	(0.245)
Intrinsic property characteristics	No	Yes	Yes	Yes
Extrinsic property characteristics	No	No	Yes	Yes
Time fixed effects	No	No	No	Yes
Number of observations	812	812	788	788
Adjusted R-squared	0.370	0.769	0.833	0.915

Notes: The dependent variable is the natural logarithm of the neighbourhood-average residential real estate value. Livability is measured as the subjective livability rating of the year prior to the transaction year. All variables are measured at the neighbourhood level. The standard errors are clustered at the neighbourhood-year level. The standard errors are given between parentheses. The level of significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

The addition of the extrinsic property characteristics to the model leads to the results in column (12). By adding the extrinsic property characteristics, the effect of subjective livability on residential real estate values decreased compared to the results of column (11). In this model, on average, a one-unit increase in the average subjective livability score of a neighborhood a year prior to the transaction year of the properties results in a 7.68 percent increase of the average residential real estate value in that neighborhood. The estimate is significant at the 1 percent level. The addition of the extrinsic property characteristics to the model raises the adjusted R-squared from 76.9 percent to 83.3 percent. This suggests that the extrinsic property characteristics helped to explain the variation in the dependent variable.

Column (13) represents the addition of the time fixed effects to the model. By adding the time fixed effects, the effect of subjective livability on residential real estate values decreased compared to the results of column (12). In this model, on average, a one-unit increase in the average subjective livability score of a neighborhood a year prior to the transaction year of the properties results in a 5.76 percent increase of the average residential real estate value in that neighborhood. The estimate is significant at the 1 percent level. The addition of the time fixed effects to the model raised the adjusted R-squared from 83.3 percent to 91.5 percent. This suggests that the time fixed effects helped to explain the variation in the dependent variable.

Airbnb activity and subjective livability predicting residential real estate values

To determine if the mediator completely mediates the relationship between the independent and dependent variable, a regression where Airbnb reviews and subjective livability predict residential real estate values is performed. The regression results are shown in table 7.

Column (14) shows the basic regression with Airbnb reviews and subjective livability as the independent variables and residential real estate values as the dependent variable. The results suggest that Airbnb reviews have a positive effect on residential real estate values; on average, a 1 percent increase in Airbnb reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.095 percent increase of the average residential real estate value in that neighborhood. Furthermore, the results suggest that subjective livability has a positive effect on residential real estate values; on average, a one-unit increase in the average subjective livability score of a neighborhood a year prior to the transaction year of the properties results in a 39.38 percent increase of the average residential real estate value in that neighborhood. The estimates are significant at the 1 percent level. The associated adjusted R-squared, explaining how much of the variance in the dependent variable can be explained by the model, is only 42.2 percent.

Table 7
Baseline regression results: the effect of all Airbnb reviews and subjective livability on residential real estate values

	(14)	(15)	(16)	(17)	(18)
	Basic	Intrinsic property characteristics	Extrinsic property characteristics	Time fixed effects	IV regression
Reviews - All (*ln*)	0.095***	0.101***	0.070***	0.040***	0.040***
	(0.015)	(0.010)	(0.008)	(0.007)	(0.009)
livability	0.332***	0.164***	0.084***	0.062***	0.066***
	(0.025)	(0.015)	(0.019)	(0.017)	(0.011)
Surface area in m^2 (*ln*)		0.958***	1.020***	0.929***	0.933***
		(0.035)	(0.037)	(0.036)	(0.023)
Building period - 1500-1905		0.315***	0.178***	0.271***	0.276***
		(0.054)	(0.049)	(0.046)	(0.030)
Building period - 1906-1944		0.252***	0.183***	0.224***	0.225***
		(0.042)	(0.038)	(0.035)	(0.020)
Building period - 1945-1970		0.056	0.022	0.056	0.054**
		(0.049)	(0.040)	(0.038)	(0.022)
Building period - 1991-2020		0.053	0.043	0.085**	0.086***
		(0.046)	(0.038)	(0.035)	(0.021)
Maintenance - Good		0.413***	0.304***	0.427***	0.436***
		(0.099)	(0.071)	(0.058)	(0.052)
Maintenance - Moderate		0.152	0.146**	0.201***	0.205***
		(0.094)	(0.066)	(0.055)	(0.047)
Non-Western			-0.001	-0.003***	-0.003***
			(0.001)	(0.001)	(0.001)
Education - Low			-0.171	-0.426***	-0.410***
			(0.154)	(0.125)	(0.099)
Education - Mid			-0.954***	-0.778***	-0.748***
			(0.147)	(0.115)	(0.080)
Unemployment			0.002	0.009***	0.010***
			(0.003)	(0.002)	(0.002)
Household - With children			-0.006***	-0.004***	-0.004***
			(0.001)	(0.001)	(0.001)
Constant	9.902***	6.547***	7.603***	7.890***	8.290***
	(0.168)	(0.196)	(0.244)	(0.232)	(0.182)
Intrinsic property characteristics	No	Yes	Yes	Yes	Yes
Extrinsic property characteristics	No	No	Yes	Yes	Yes
Time fixed effects	No	No	No	Yes	Yes
Number of observations	812	812	788	788	765
Adjusted R-squared	0.422	0.807	0.849	0.920	0.919

Notes: The dependent variable is the natural logarithm of the neighbourhood-average residential real estate value. The number of Airbnb reviews is measured as the natural logarithm of the total number of Airbnb reviews of the year prior to the transaction year. Livability is measured as the subjective livability rating of the year prior to the transaction year. IV regression: The number of Airbnb reviews is instrumented by the natural logarithm of the number of horeca establishments and the natural logarithm of the number of cultural establishments. All variables are measured at the neighbourhood-year level. The standard errors are clustered at the neighbourhood level. The standard errors are given between parentheses. The level of significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

Column (15) represents the addition of the intrinsic property characteristics to the model. By adding the intrinsic property characteristics, the effect of Airbnb reviews on residential real estate values increased and the effect of subjective livability on residential real estate values decreased compared to the results of column (14). In this model, on average, a 1 percent increase in Airbnb reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.101 percent increase of the average residential real estate value in that neighborhood and a one-unit increase in the average subjective livability score of a neighborhood a year prior to the transaction year of the properties results in a 17.82 percent increase of the average residential real estate value in that neighborhood. The estimates are significant at the 1 percent level. The addition of the intrinsic property characteristics to the model raises the adjusted R-squared from

42.2 percent to 80.7 percent. This suggests that the intrinsic property characteristics helped to explain the variation in the dependent variable.

The addition of the extrinsic property characteristics to the model leads to the results in column (16). By adding the extrinsic property characteristics, the effect of Airbnb reviews and subjective livability on residential real estate values decreased compared to the results of column (15). In this model, on average, a 1 percent increase in Airbnb reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.07 percent increase of the average residential real estate value in that neighborhood and a one-unit increase in the average subjective livability score of a neighborhood a year prior to the transaction year of the properties results in a 8.76 percent increase of the average residential real estate value in that neighborhood. The estimates are significant at the 1 percent level. The addition of the extrinsic property characteristics to the model raises the adjusted R-squared from 80.7 percent to 84.9 percent. This suggests that the extrinsic property characteristics helped to explain the variation in the dependent variable.

Column (17) represents the addition of the time fixed effects to the model. By adding the time fixed effects, the effect of Airbnb reviews and subjective livability on residential real estate values decreased compared to the results of column (16). In this model, on average, a 1 percent increase in Airbnb reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.04 percent increase of the average residential real estate value in that neighborhood and a one-unit increase in the average subjective livability score of a neighborhood a year prior to the transaction year of the properties results in a 6.4 percent increase of the average residential real estate value in that neighborhood. The estimates are significant at the 1 percent level. The addition of the time fixed effects to the model raises the adjusted R-squared from 84.9 percent to 92 percent. This suggests that the time fixed effects helped to explain the variation in the dependent variable.

Reverse causality

As mentioned in the methodology section, it was assumed that reverse causality could exists between Airbnb activity and residential real estate values, and between Airbnb activity and subjective livability. From the Durbin-Wu-Hausman test, it becomes clear that there exists endogeneity in the results column (8) of table 5, which is the regression with Airbnb reviews as the independent variable and subjective livability as the dependent variable.

To mitigate the effect of endogeneity, an instrumental variables approach is taken. By taking an instrumental variables approach, any bias that might have been present due to the endogenous variable, would be erased. However, finding a suitable instrumental variable is not always easy. An instrumental variable has to be correlated to the independent variable and unrelated to the dependent variable (Ullah et al., 2021). In the current research, the number of horeca establishments and the number of cultural establishments were used as instrumental variables. The chosen instrumental variables were correlated with Airbnb reviews, but unrelated to the dependent variable, as shown in the correlation matrices in appendix H. The results of the IV regressions are set out below.

Column (5) of table 4 defines the IV regression of Airbnb reviews and residential real estate values. The IV regression returned results nearly similar to the results of column (4). In this model, on average, a 1 percent increase in Airbnb reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.038 percent increase of the average residential real estate value in that neighborhood. The estimate is significant at the 1 percent level. The adjusted R-squared remained high at 91.5 percent, suggesting that the IV regression explained the variation in the dependent variable as good as the model in column (4).

Column (9) of table 5 defines the IV regression of Airbnb reviews and subjective livability. The IV regression returned results different from the results of column (8). In this model, on average, a 1 percent increase in Airbnb reviews in a neighborhood results in a 0.00321 unit decrease of the average subjective livability score of that neighborhood. The estimate is significant at the 1 percent level. The adjusted R-squared remained relatively high at 67 percent, suggesting that the IV regression explained the variation in the dependent variable almost as good as the model in column (8).

Column (18) of table 7 defines the IV regression of Airbnb reviews, subjective livability and residential real estate values. The IV regression returned results nearly similar to the results of column (17). In this model, on average, a 1 percent increase in Airbnb reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.040 percent increase of the average residential real estate value in that neighborhood and a one-unit increase in the average subjective livability score of a neighborhood a year prior to the transaction year of the properties results in a 6.82 percent increase of the average residential real estate value in that neighborhood. The estimates are significant at the 1 percent level. The adjusted R-squared remained high at 91.9 percent, suggesting that the IV regression explained the variation in the dependent variable as good as the model in column (17).

To conclude, according to the Durbin-Wu-Hausman test, Airbnb reviews is an endogenous variable in the regression with Airbnb reviews as the independent variable and subjective livability as the dependent variable. Therefore, it would be wise to use the results of the IV regression as a definitive result for this research. The IV regression results will be used to calculate the remaining equations and compared to the results of the robustness checks.

The mediating effect of subjective livability

Within the mediation model used in this paper it is possible for the independent variable to influence the dependent variable in two different ways, namely directly and indirectly. To get a better understanding of the relationships between the variables Airbnb reviews, subjective livability and residential real estate values, the direct and indirect effect of Airbnb reviews on residential real estate values are calculated. Furthermore, it is of importance to check if the indirect effect of Airbnb reviews on residential real estate values is statistically significant. The Sobel test will be used to check if the indirect effect is statistically significant. At last, this research will calculate if the indirect effect is economically significant by estimating what percentage of the total effect is mediated through the mediator subjective livability.

According to Baron and Kenny (1986) the direct effect of Airbnb reviews on residential real estate values is equal to the first step of the mediation model. Specifically, one should look at column (5) of table 4 for the direct effect of Airbnb reviews on residential real estate values. From column (5) it follows that, on average, a 1 percent increase in Airbnb reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.038 percent increase of the average residential real estate value in that neighborhood. This estimate is significant at the 1 percent level.

Calculating the indirect effect of Airbnb reviews on residential real estate values is more cumbersome. To calculate the indirect effect, the product of coefficients method is used. Formula (5) in the methodology section states the formula for the product of coefficients method. The product of coefficients method states that the indirect effect can be calculated by $a * b$ in which a represents the effect of Airbnb reviews on subjective livability and b represents the effect of subjective livability on residential real estate values. From column (9) of table 5 it follows that a = -0.321 and from column (13) of table 6 it follows that b = 0.056. The indirect can thus be calculated as -0.321 x 0.056 = -0.01798. This means that, on average, a 1 percent increase in Airbnb reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.01798 percent decrease of the average residential real estate value in that neighborhood.

To calculate the statistical significance of the indirect effect, the Sobel test is used. Formula (7) in the methodology section states the formula for the Sobel test. To calculate the statistical significance of the indirect effect, the following estimates are needed; a which is the effect of Airbnb reviews on subjective livability, b which is the effect of subjective livability on residential real estate values, s_a which is the standard error of a and s_b which is the standard error of b. From column (9) of table 5 it follows that a = -0.321 and s_a = 0.045. From column (13) of table 6 it follows that b = 0.056 and s_b= 0.018. From the Sobel test it follows that the p-value of the estimate of the indirect effect is 0.004349. This means that the estimate of the indirect effect is significant at the 1 percent level.

Furthermore, it is important to know if the indirect effect has any economic significance. To calculate if the indirect effect is economically significant, this paper will calculate what percentage of the total effect can be assigned as going through path $a * b$. This can be done with formula (6) stated in the methodology section. From the above calculations, it is known that, on average, a 1 percent increase in Airbnb reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.01798 percent decrease of the average residential real estate value in that neighborhood. This is the effect that goes through path $a * b$. From column (5) of table 4 it follows that, on average, a 1 percent increase in Airbnb reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.038 percent increase of the average residential real estate value in that neighborhood. This is the total effect, otherwise known as path c. It then follows that -0.01798 / 0.038 = -47.30 percent of the total effect goes through path $a * b$. Noticeably, the estimate is negative. The estimate indicates that there exists inconsistent mediation in this mediation model; the direct effect of Airbnb reviews on residential real estate values is positive, while the indirect effect of Airbnb reviews on residential real estate values - through the mediator subjective livability – is negative. It can therefore be concluded that the mediator subjective livability has a dampening effect on the relationship between Airbnb reviews and residential real estate values.

DISCUSSION

In this section, some robustness checks will be performed. First, Airbnb listings will be used to measure Airbnb activity instead of Airbnb reviews. Second, the Airbnb reviews will be divided between entire home reviews and private room reviews to check if different listing types have a different effect on subjective livability and residential real estate values. The results of the robustness checks will be compared to the main results of this paper.

Airbnb listings

To check the robustness of the main results, Airbnb listings will be used as a proxy for Airbnb activity instead of Airbnb reviews. For each step of the mediation model, the main results of this paper will be compared to the results of the robustness check.

Column (22) of table 8 in appendix B represents the regression with Airbnb listings as the independent variable and residential real estate values as the dependent variable. Furthermore, intrinsic property characteristics, extrinsic property characteristics and time fixed effects are added as control variables. The results suggest that Airbnb listings have a positive effect on residential real estate values; on average, a 1 percent increase in Airbnb listings in a neighborhood a year prior to the transaction year of the properties results in a 0.047 percent increase of the average residential real estate value in that neighborhood. The estimate is significant at the 1 percent level. The associated adjusted R-squared is 91.8 percent. Noticeably, the estimate for Airbnb listings is higher compared to the estimate for Airbnb reviews, which was 0.038 percent.

Column (25) of table 9 in appendix C represents the regression with Airbnb listings as the independent variable and subjective livability as the dependent variable. Furthermore, neighborhood characteristics and time fixed effects are added as control variables. The results suggest that Airbnb listings have a negative effect on subjective livability; on average, a 1 percent increase in Airbnb listings in a neighborhood results in a 0.0013 unit decrease of the average subjective livability score of that neighborhood. The estimate is significant at the 1 percent level. The associated adjusted R-squared is 71.4 percent. Noticeably, the estimate for Airbnb listings is lower in magnitude compared to the estimate for Airbnb reviews, which was -0.00321.

Column (29) of table 10 in appendix D represents the regression with Airbnb listings and subjective livability as the independent variables and residential real estate values as the dependent variable. Furthermore, intrinsic property characteristics, extrinsic property characteristics and time fixed effects are added as control variables. The results suggest that Airbnb listings have a positive effect on residential real estate values; on average, a 1 percent increase in Airbnb listings in a neighborhood a year prior to the transaction year of the properties results in a 0.049 percent increase of the average residential real estate value in that neighborhood. Furthermore, the results suggest that subjective livability has a positive effect on residential real estate values; on average, a one-unit increase in the average subjective livability score of a neighborhood a year prior to the transaction year of the properties results in a 6.18 percent increase of the average residential real estate value in that neighborhood. The estimates are significant at the 1 percent level. The associated adjusted R-squared is 92.1 percent. Noticeably, the estimate for Airbnb listings is higher compared to the estimate for Airbnb reviews, which was 0.040 percent, while the estimate for subjective livability here is lower in magnitude compared to the estimate of the main results, which was 6.82 percent.

To calculate the indirect effect, formula (5) of the methodology section is used. From column (25) of table 9 in appendix C it follows that a = -0.13 and from column (13) of table 6 it follows that b = 0.056. The indirect effect can thus be calculated as -0.13 x 0.056 = -0.00728. According to the Sobel test, the estimate is statistically significant at the 1 percent level. The estimate for the indirect effect is lower in magnitude compared to the estimate of the main results, which was -0.01798. To calculate the economic significance, formula (6) of the methodology section is used. From column (22) of table 8 in appendix B it follows that c = 0.047. The economic significance of the indirect effect can thus be calculated as -0.13 x 0.056 / 0.047 = -15.49 percent. The estimate for the economic significance of the indirect effect is lower in magnitude compared to the estimate of the main results, which was -47.30 percent.

Although most the results of this section are lower in magnitude than the main results, the same conclusions can be drawn when Airbnb listings are taken as proxy for Airbnb activity instead of Airbnb reviews.

Entire home reviews and private room reviews

Another approach to test the validity of the main results is to divide Airbnb reviews into two categories, namely entire home reviews and private room reviews. These categories are then used as proxy for Airbnb activity instead of Airbnb reviews. For each step of the mediation model, the main results of this paper will be compared to the results of the robustness check.

Column (33) of table 11 in appendix E represents the regression with entire home reviews and private room reviews as the independent variables and residential real estate values as the dependent variable. Furthermore, intrinsic property characteristics, extrinsic property characteristics and time fixed effects are added as control variables. The results suggest that entire home reviews have a positive effect on residential real estate values; on average, a 1 percent increase in entire home reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.039 percent increase of the average residential real estate value in that neighborhood. The estimate is significant at the 1 percent level. The associated adjusted R-squared is 91.9 percent. Noticeably, the estimate for private room reviews is not significant, while the estimate for entire home reviews is slightly higher compared to the estimate of the main results, which was 0.038 percent.

Column (36) of table 12 in appendix F represents the regression with entire home reviews and private room reviews as the independent variables and subjective livability as the dependent variable. Furthermore, neighborhood characteristics and time fixed effects are added as control variables. The results suggest that entire home reviews have a negative effect on subjective livability; on average, a 1 percent increase in entire home reviews in a neighborhood results in a 0.00059 unit decrease of the average subjective livability score of that neighborhood. The estimate is significant at the 1 percent level. Furthermore, the results suggest that private room reviews have a negative effect on subjective livability; on average, a 1 percent increase in private room reviews in a neighborhood results in a 0.00034 unit decrease of the average subjective livability score of that neighborhood. The estimate is significant at the 5 percent level. The associated adjusted R-squared is 71.3 percent. The sum of the estimates is -0.00093. Noticeably, the sum of the estimates here is lower in magnitude compared to the estimate of the main results, which was -0.00321.

Column (40) of table 13 in appendix G represents the regression with entire home reviews, private room reviews and subjective livability as the independent variables and residential real estate values as the dependent variable. Furthermore, intrinsic property characteristics, extrinsic property characteristics and time fixed effects are added as control variables. The results suggest that entire home reviews have a positive effect on residential real estate values; on average, a 1 percent increase in entire home reviews in a neighborhood a year prior to the transaction year of the properties results in a 0.040 percent increase of the average residential real estate value in that neighborhood. Furthermore, the results suggest that subjective livability has a positive effect on residential real estate values; on average, a one-unit increase in the average subjective livability score of a neighborhood a year prior to the transaction year of the properties results in a 6.29 percent increase of the average residential real estate value in that neighborhood. The estimates are significant at the 1 percent level. The associated adjusted R-squared is 92.2 percent. Noticeably, the estimate for private room reviews is not significant, while the estimate for entire home reviews is equal to the estimate of the main results. Furthermore, the estimate for subjective livability is lower in magnitude compared to the estimate of the main results, which was 6.82 percent.

To calculate the indirect effect, formula (5) of the methodology section is used. From column (36) of table 12 in appendix F it follows that a = -0.059 + -0.034 = -0.093. Here, the estimates of entire home reviews and private room reviews are added together. From column (13) of table 6 it follows that b = 0.056. The indirect effect can thus be calculated as -0.093 x 0.056 = -0.00521. The estimate for the indirect effect is lower in magnitude compared to the estimate of the main results, which was -0.01798. To test the statistical significance, the Sobel test is used. Because the Sobel test only allows one independent variable, the statistical significance is tested for entire home reviews and private room reviews separately. According to the Sobel test, the estimates are statistically significant at the 5 percent level. Unfortunately, it is not possible to calculate the economic significance. The estimates for private room reviews are statistically insignificant in some steps of the mediation model, which makes it invalid to calculate the economic significance.

To conclude, it is noticeable that the estimate of private room reviews is statistically insignificant in column (33) and column (40). This could suggest that private room reviews do not have an effect on residential real estate values, while entire home reviews do have an effect on residential real estate values. Furthermore, it can be concluded that the estimates for entire home reviews are approximately the same as the estimates of the main results, again suggesting that entire home reviews are the main reason for rising residential real estate values in Amsterdam, rather than both entire home reviews and private room reviews. This is not unsurprising as the owner of the property is not present when the entire home is rented out (Guttentag, 2018).

CONCLUSION

In this study, the relationships between Airbnb activity, subjective livability and residential real estate values have been investigated. Earlier research investigating the effect of Airbnb activity on residential real estate values found a positive effect. Furthermore, it also became apparent from previous studies that subjective livability has a positive effect on residential real estate values. However, research on the relationship between Airbnb activity and subjective livability was mainly qualitative of nature. This study attempted to bring these concepts together in one model, namely the mediation model proposed by Baron and Kenny (1986), to shed light on the interplay between the three variables.

The results of this study indicate that Airbnb has a direct positive effect on residential real estate values; for every 1 percent increase in Airbnb reviews, residential real estate values increase by 0.038 percent. The results also imply that Airbnb has a negative effect on subjective livability; for every 1 percent increase in Airbnb reviews, subjective livability decreases with 0.00321 units. Furthermore, the results indicate that subjective livability has a positive effect on residential real estate values; for every one-unit increase in subjective livability, residential real estate values increase by 5.76 percent. This paper is also able to answer the research question "Does subjective livability have a mediating effect on the relationship between Airbnb activity and residential real estate values?". The above suggests that subjective livability mediates the direct effect of Airbnb activity on residential real estate values and that the indirect effect of Airbnb activity on residential real estate values – through the mediator subjective livability – dampens the direct effect by 47.30 percent.

The findings of this paper confirm that subjective livability has a dampening effect on the relationship between Airbnb activity and residential real estate values. However, as the effect is dampened by 47.30 percent, the total effect of Airbnb activity on residential real estate values is still positive. Airbnb activity has therefore a positive total effect on residential real estate values.

Policy Recommendations

Rising real estate values are important for wealth creation and the expansion of the tax base for a government. However, in the Netherlands, municipalities do not have to worry so much about income, as their income is supplemented by the Gemeentefonds of the national government (Rijksoverheid, 2022). Municipalities can thus focus on other important affairs. As can be concluded by the main results, Airbnb activity has a negative effect on livability and a positive effect on residential real estate values. On one hand, as the municipality of Amsterdam already has to deal with decreasing affordability of housing and livability, it would be of interest to focus on mitigating the negative effects of Airbnb on housing affordability and livability (Barker, 2020).

On the other hand, the municipality of Amsterdam does not want to forbid Airbnb altogether, because of its undeniable positive effect on the economy (Jordan and Moore, 2018). This research therefore suggests that the municipality of Amsterdam should optimize existing legislation, by introducing a permit system, which would allow a certain amount of Airbnb listings in certain neighborhoods. This could increase the total amount of Airbnb listings, while distributing the burdens that come with the increasing number of tourists over a greater surface area. In Amsterdam, the same is done for houses that accommodate students. Only a certain percentage of the total housing stock can be converted to student accommodation to prevent the studentification of a neighborhood, which could drive away other groups of residents (Municipality of Amsterdam, 2021b). Introducing such a permit system could thus be a viable option to apply to Airbnb listings too.

Furthermore, in the discussion section, the total effect of Airbnb activity is divided between the effect of entire homes and private rooms. From that analysis, it becomes apparent that the effect of Airbnb activity on residential real estate is mainly driven by entire homes and that the effect of Airbnb activity on livability is stronger for entire homes than for private rooms. The municipality should take these findings into account when it comes to new legislation regarding Airbnb. To increase the positive effects of Airbnb, which are mainly economical, it could be of interest to decrease the amount of entire home listings and increase the amount of private room listings, as private room listings do not have as much of a negative effect on housing affordability and livability as entire home listings. The municipality of Amsterdam could accomplish this by making it mandatory to register the listing type when the home owner registers for a permit and check if the specified listing type corresponds to the listing type of the ad on the Airbnb platform.

Limitations and future research

The current study had some limitations. According to the Breusch-Pagan / Cook-Weisberg test and White's test, there exists heteroskedasticity in some of the regression results. Heteroskedasticity leads to a violation of the OLS assumption of constant variance (White, 1980). This paper used neighborhood clustered standard errors to overcome the problem of heteroskedasticity (Cameron and Miller, 2015). Furthermore, the variables residential real estate values and Airbnb activity are transformed into a natural log, so that the effect of extreme values is reduced. Unfortunately, the Breusch-Pagan / Cook-Weisberg test and White's test cannot be used after using clustered standard errors. Therefore, heteroskedasticity in the data cannot be ruled out.

Furthermore, Ramsey's RESET test indicates that the model is not correctly specified. A model that is not correctly specified could potentially lead to results that are not reliable (Ramsey, 1969). Future research could try to use a non-linear functional form to approximate the relationships.

Data on subjective livability and the control variables that were provided by several governmental agencies had been provided at the neighborhood-level to protect the privacy of individuals. This research chose to aggregate all other data at the neighborhood-level, so that all data was measured at the same level of aggregation. Unfortunately, this leads to a loss of detail. Future research could focus on a multilevel model or a structured equation model to retain the detail that is in the residential real estate data and Airbnb data (e.g., Preacher, Zyphur and Zhang, 2010).

This study used a single variable as the measure of subjective livability. However, livability consists of multiple factors. For example, the Leefbaarometer consists of 100 individual variables (Ministry of Internal Affairs and Kingdom Relations, 2016). It would be beneficial to governmental bodies to get a better understanding of the livability factors that are most affected by Airbnb activity, so that they can focus their effort at introducing policies specifically addressing those issues.

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APPENDICES

Appendix A: Descriptive statistics NVM

Table 3
Descriptive statistics NVM

	2016						
	Mean	**Median**	**Std. Dev.**	**Min.**	**Max.**	**25th percentile**	**75th percentile**
Transaction price	414130	310000	386078	64000	6200000	230000	455000
Surface area in m^2	89,53	77,00	54,95	9,00	880,00	57,00	104,00
Building period (%)							
1500-1905	18,66		38,96				
1906-1944	34,03		47,38				
1945-1970	13,89		34,58				
1971-1990	12,84		33,45				
1991-2020	20,59		40,44				
Maintenance (%)							
Good	19,31		39,47				
Moderate	74,67		43,49				
Bad	6,03		23,80				
Transaction date category (%)							
2016-01	23,04		42,11				
2016-02	28,09		44,95				
2016-03	23,51		42,41				
2016-04	25,36		43,51				
Number of observations	10385						
	2018						
	Mean	**Median**	**Std. Dev.**	**Min.**	**Max.**	**25th percentile**	**75th percentile**
Transaction price	533805	412640	454288	68000	10250000	318000	590000
Surface area in m^2	91,56	79,00	57,75	10,00	1954,00	58,00	107,00
Building period (%)							
1500-1905	18,15		38,54				
1906-1944	34,91		47,67				
1945-1970	14,83		35,54				
1971-1990	11,36		31,73				
1991-2020	20,75		40,56				
Maintenance (%)							
Good	18,15		38,54				
Moderate	72,97		44,42				
Bad	8,89		28,46				
Transaction date category (%)							
2018-01	22,45		41,73				
2018-02	25,83		43,77				
2018-03	23,65		42,50				
2018-04	28,07		44,94				
Number of observations	7720						

Table 3 (continued)
Descriptive statistics NVM

	2020						
	Mean	**Median**	**Std. Dev.**	**Min.**	**Max.**	**25th percentile**	**75th percentile**
Transaction price	584857	480000	408150	89500	8800000	365000	672500
Surface area in m^2	97,85	90,00	48,38	10,00	558,00	66,00	118,00
Building period (%)							
1500-1905	20,52		40,39				
1906-1944	33,18		47,09				
1945-1970	12,75		33,36				
1971-1990	11,23		31,57				
1991-2020	22,32		41,64				
Maintenance (%)							
Good	21,39		41,01				
Moderate	72,55		44,63				
Bad	6,05		23,85				
Transaction date category (%)							
2020-01	16,77		37,36				
2020-02	26,42		44,09				
2020-03	27,01		44,40				
2020-04	29,81		45,74				
Number of observations	7465						

	Total						
	Mean	**Median**	**Std. Dev.**	**Min.**	**Max.**	**25th percentile**	**75th percentile**
Transaction price	500104	390000	420605	64000	10250000	285000	572500
Surface area in m^2	92,57	81,00	54,12	9,00	1954,00	59,00	110,00
Building period (%)							
1500-1905	19,05		39,27				
1906-1944	34,05		47,39				
1945-1970	13,84		34,53				
1971-1990	11,92		32,40				
1991-2020	21,14		40,83				
Maintenance (%)							
Good	19,57		39,67				
Moderate	73,54		44,12				
Bad	6,90		25,34				
Transaction date category (%)							
2016-01	9,36		29,13				
2016-02	11,41		31,79				
2016-03	9,55		29,39				
2016-04	10,30		30,40				
2018-01	6,78		25,14				
2018-02	7,80		26,81				
2018-03	7,14		25,75				
2018-04	8,47		27,85				
2020-01	4,90		21,58				
2020-02	7,71		26,68				
2020-03	7,88		26,95				
2020-04	8,70		28,19				
Number of observations	25570						

Appendix B: The effect of all Airbnb listings on residential real estate values

Table 8
Alternative regression results: the effect of all Airbnb listings on residential real estate values

	(19)	(20)	(21)	(22)
	Basic	**Intrinsic property characteristics**	**Extrinsic property characteristics**	**Time fixed effects**
Listings - All (*ln*)	0.157***	0.134***	0.084***	0.047***
	(0.017)	(0.011)	(0.010)	(0.009)
Surface area in m^2 (*ln*)		1.131***	1.065***	0.954***
		(0.039)	(0.037)	(0.037)
Building period - 1500-1905		0.390***	0.175***	0.272***
		(0.053)	(0.047)	(0.045)
Building period - 1906-1944		0.294***	0.162***	0.213***
		(0.044)	(0.039)	(0.036)
Building period - 1945-1970		-0.004	0.001	0.042
		(0.055)	(0.039)	(0.038)
Building period - 1991-2020		0.020	0.023	0.072**
		(0.050)	(0.037)	(0.034)
Maintenance - Good		0.379***	0.275***	0.403***
		(0.105)	(0.066)	(0.055)
Maintenance - Moderate		0.129	0.134**	0.188***
		(0.097)	(0.061)	(0.052)
Non-Western			-0.003***	-0.004***
			(0.001)	(0.001)
Education - Low			-0.252	-0.508***
			(0.154)	(0.126)
Education - Mid			-0.939***	-0.786***
			(0.148)	(0.117)
Unemployment			0.003	0.010***
			(0.003)	(0.002)
Household - With children			-0.005***	-0.003***
			(0.001)	(0.001)
Constant	12.417***	7.149***	8.220***	8.377***
	(0.064)	(0.213)	(0.195)	(0.197)
Intrinsic property characteristics	No	Yes	Yes	Yes
Extrinsic property characteristics	No	No	Yes	Yes
Time fixed effects	No	No	No	Yes
Number of observations	812	812	788	788
Adjusted R-squared	0.153	0.778	0.847	0.918

Notes : The dependent variable is the natural logarithm of the neighbourhood-average residential real estate value. The number of Airbnb listings is measured as the natural logarithm of the total number of Airbnb listings of the year prior to the transaction year. All variables are measured at the neighbourhood-year level. The standard errors are clustered at the neighbourhood level. The standard errors are given between parentheses. The level of significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

Appendix C: The effect of all Airbnb listings on subjective livability

Table 9
Alternative regression results: the effect of all Airbnb listings on subjective livability

	(23) Basic	**(24)** Neighborhood characteristics	**(25)** Time fixed effects
Listings - All (*ln*)	0.237***	-0.102***	-0.130***
	(0.021)	(0.024)	(0.026)
Non-Western		-0.021***	-0.021***
		(0.002)	(0.002)
Education - Low		-1.901***	-1.897***
		(0.230)	(0.231)
Education - Mid		-1.404***	-1.477***
		(0.226)	(0.230)
Household - One adult		0.071***	0.072***
		(0.020)	(0.020)
Household - One adult with child(ren)		0.104***	0.103***
		(0.020)	(0.020)
Household - More than one adult without child(ren)		0.065***	0.065***
		(0.021)	(0.021)
Household - More than one adult with child(ren)		0.076***	0.077***
		(0.020)	(0.020)
Duration of residence (years)		0.038***	0.037***
		(0.007)	(0.007)
Physical environment rating		-0.775***	-0.836***
		(0.127)	(0.129)
Number of services (*ln*)		0.142***	0.165***
		(0.031)	(0.032)
Constant	6.760***	1.098	1.062
	(0.076)	(1.992)	(1.983)
Neighborhood characteristics	No	Yes	Yes
Time fixed effects	No	No	Yes
Number of observations	812	800	800
Adjusted R-squared	0.136	0.711	0.714

Notes: The dependent variable is the subjective livability rating of the year prior to the transaction year. The number of Airbnb listings is measured as the natural logarithm of the total number of Airbnb listings of the year prior to the transaction year. All variables are measured at the neighbourhood-year level. The standard errors are given between parentheses. The level of significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

Appendix D: The effect of all Airbnb listings and subjective livability on residential real estate values

Table 10
Alternative regression results: the effect of all Airbnb listings and subjective livability on residential real estate values

	(26) Basic	**(27)** Intrinsic property characteristics	**(28)** Extrinsic property characteristics	**(29)** Time fixed effects
Listings - All (*ln*)	0.077***	0.119***	0.086***	0.049***
	(0.016)	(0.010)	(0.009)	(0.008)
livability	0.338***	0.151***	0.080***	0.060***
	(0.027)	(0.015)	(0.020)	(0.017)
Surface area in m^2 (*ln*)		1.013***	1.058***	0.951***
		(0.035)	(0.037)	(0.036)
Building period - 1500-1905		0.304***	0.177***	0.272***
		(0.053)	(0.049)	(0.046)
Building period - 1906-1944		0.213***	0.163***	0.213***
		(0.042)	(0.039)	(0.036)
Building period - 1945-1970		0.047	0.017	0.054
		(0.048)	(0.041)	(0.039)
Building period - 1991-2020		0.034	0.039	0.083**
		(0.044)	(0.038)	(0.035)
Maintenance - Good		0.386***	0.295***	0.417***
		(0.089)	(0.068)	(0.055)
Maintenance - Moderate		0.153*	0.147**	0.198***
		(0.084)	(0.062)	(0.052)
Non-Western			-0.001	-0.003***
			(0.001)	(0.001)
Education - Low			-0.090	-0.382***
			(0.153)	(0.125)
Education - Mid			-0.840***	-0.718***
			(0.148)	(0.114)
Unemployment			0.002	0.009***
			(0.003)	(0.002)
Household - With children			-0.006***	-0.004***
			(0.001)	(0.001)
Constant	10.136***	6.593***	7.541***	7.867***
	(0.177)	(0.191)	(0.249)	(0.229)
Intrinsic property characteristics	No	Yes	Yes	Yes
Extrinsic property characteristics	No	No	Yes	Yes
Time fixed effects	No	No	No	Yes
Number of observations	812	812	788	788
Adjusted R-squared	0.402	0.814	0.852	0.921

Notes: The dependent variable is the natural logarithm of the neighbourhood-average residential real estate value. The number of Airbnb listings is measured as the natural logarithm of the total number of Airbnb listings of the year prior to the transaction year. Livability is measured as the subjective livability rating of the year prior to the transaction year. All variables are measured at the neighbourhood-year level. The standard errors are clustered at the neighbourhood level. The standard errors are given between parentheses. The level of significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

Appendix E: The effect of Apartment and Private room Airbnb reviews on residential real estate values

Table 11
Alternative regression results: the effect of Apartment and Private room Airbnb reviews on residential real estate values

	(30)	**(31)**	**(32)**	**(33)**
	Basic	**Intrinsic property characteristics**	**Extrinsic property characteristics**	**Time fixed effects**
Reviews - Entire homes (*ln*)	0.105***	0.090***	0.041***	0.039***
	(0.013)	(0.008)	(0.008)	(0.006)
Reviews - Private rooms (*ln*)	0.040***	0.012	0.022***	-0.002
	(0.014)	(0.008)	(0.006)	(0.005)
Surface area in m^2 (*ln*)		1.105***	1.027***	0.948***
		(0.037)	(0.036)	(0.037)
Building period - 1500-1905		0.380***	0.178***	0.262***
		(0.053)	(0.046)	(0.044)
Building period - 1906-1944		0.314***	0.180***	0.217***
		(0.043)	(0.037)	(0.035)
Building period - 1945-1970		-0.001	0.002	0.041
		(0.054)	(0.038)	(0.037)
Building period - 1991-2020		0.037	0.029	0.072**
		(0.048)	(0.036)	(0.034)
Maintenance - Good		0.348***	0.267***	0.385***
		(0.111)	(0.070)	(0.055)
Maintenance - Moderate		0.113	0.121*	0.183***
		(0.102)	(0.065)	(0.053)
Non-Western			-0.003***	-0.004***
			(0.001)	(0.001)
Education - Low			-0.339**	-0.523***
			(0.154)	(0.122)
Education - Mid			-1.010***	-0.785***
			(0.149)	(0.114)
Unemployment			0.003	0.009***
			(0.003)	(0.002)
Household - With children			-0.005***	-0.003***
			(0.001)	(0.001)
Constant	12.249***	7.224***	8.396***	8.391***
	(0.072)	(0.207)	(0.199)	(0.196)
Intrinsic property characteristics	No	Yes	Yes	Yes
Extrinsic property characteristics	No	No	Yes	Yes
Time fixed effects	No	No	No	Yes
Number of observations	812	812	788	788
Adjusted R-squared	0.187	0.775	0.845	0.919

Notes : The dependent variable is the natural logarithm of the neighbourhood-average residential real estate value. The number of Airbnb entire home reviews is measured as the natural logarithm of the total number of Airbnb entire home reviews of the year prior to the transaction year. The number of Airbnb private room reviews is measured as the natural logarithm of the total number of Airbnb private room reviews of the year prior to the transaction year. All variables are measured at the neighbourhood-year level. The standard errors are clustered at the neighbourhood level. The standard errors are given between parentheses. The level of significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

Appendix F: The effect of Apartment and Private room Airbnb reviews on subjective livability

Table 12
Alternative regression results: the effect of Apartment and Private room Airbnb reviews on subjective livability

	(34) Basic	(35) Neighborhood characteristics	(36) Time fixed effects
Reviews - Entire homes (*ln*)	0.220***	-0.047***	-0.059***
	(0.017)	(0.016)	(0.016)
Reviews - Private rooms (*ln*)	-0.070***	-0.030**	-0.034**
	(0.019)	(0.013)	(0.013)
Non-Western		-0.021***	-0.021***
		(0.002)	(0.002)
Education - Low		-1.882***	-1.874***
		(0.230)	(0.231)
Education - Mid		-1.396***	-1.458***
		(0.226)	(0.232)
Household - One adult		0.072***	0.074***
		(0.020)	(0.020)
Household - One adult with child(ren)		0.105***	0.106***
		(0.021)	(0.021)
Household - More than one adult without child(ren)		0.065***	0.067***
		(0.021)	(0.021)
Household - More than one adult with child(ren)		0.077***	0.079***
		(0.020)	(0.020)
Duration of residence (years)		0.039***	0.039***
		(0.007)	(0.007)
Physical environment rating		-0.650***	-0.677***
		(0.123)	(0.123)
Number of services (*ln*)		0.133***	0.148***
		(0.030)	(0.030)
Constant	6.798***	1.075	0.922
	(0.090)	(2.002)	(2.000)
Neighborhood characteristics	No	Yes	Yes
Time fixed effects	No	No	Yes
Number of observations	812	800	800
Adjusted R-squared	0.178	0.711	0.713

Notes: The dependent variable is the subjective livability rating of the year prior to the transaction year. The number of Airbnb entire home reviews is measured as the natural logarithm of the total number of Airbnb entire home reviews of the year prior to the transaction year. The number of Airbnb private room reviews is measured as the natural logarithm of the total number of Airbnb private room reviews of the year prior to the transaction year. All variables are measured at the neighbourhood-year level. The standard errors are given between parentheses. The level of significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

Appendix G: The effect of Apartment and Private room Airbnb reviews and subjective livability on residential real estate values

Table 13

Alternative regression results: the effect of Apartment and Private room Airbnb reviews and subjective livability on residential real estate values

	(37)	(38)	(39)	(40)
	Basic	Intrinsic property characteristics	Extrinsic property characteristics	Time fixed effects
Reviews - Entire homes (*ln*)	0.030**	0.070***	0.042***	0.040***
	(0.013)	(0.008)	(0.007)	(0.006)
Reviews - Private rooms (*ln*)	0.064***	0.026***	0.025***	0.000
	(0.012)	(0.007)	(0.006)	(0.005)
livability	0.344***	0.156***	0.087***	0.061***
	(0.027)	(0.015)	(0.019)	(0.016)
Surface area in m^2 (*ln*)		0.974***	1.018***	0.944***
		(0.035)	(0.037)	(0.036)
Building period - 1500-1905		0.296***	0.177***	0.260***
		(0.050)	(0.048)	(0.046)
Building period - 1906-1944		0.234***	0.180***	0.217***
		(0.040)	(0.038)	(0.035)
Building period - 1945-1970		0.051	0.020	0.052
		(0.046)	(0.039)	(0.038)
Building period - 1991-2020		0.051	0.046	0.083**
		(0.043)	(0.037)	(0.034)
Maintenance - Good		0.377***	0.290***	0.400***
		(0.100)	(0.073)	(0.056)
Maintenance - Moderate		0.137	0.134**	0.193***
		(0.093)	(0.068)	(0.053)
Non-Western			-0.001	-0.003***
			(0.001)	(0.001)
Education - Low			-0.162	-0.395***
			(0.153)	(0.120)
Education - Mid			-0.899***	-0.715***
			(0.147)	(0.111)
Unemployment			0.002	0.008***
			(0.003)	(0.002)
Household - With children			-0.006***	-0.004***
			(0.001)	(0.001)
Constant	9.908***	6.669***	7.656***	7.874***
	(0.180)	(0.189)	(0.243)	(0.227)
Intrinsic property characteristics	No	Yes	Yes	Yes
Extrinsic property characteristics	No	No	Yes	Yes
Time fixed effects	No	No	No	Yes
Number of observations	812	812	788	788
Adjusted R-squared	0.433	0.812	0.851	0.922

Notes: The dependent variable is the natural logarithm of the neighbourhood-average residential real estate value. The number of Airbnb entire home reviews is measured as the natural logarithm of the total number of Airbnb entire home reviews of the year prior to the transaction year. The number of Airbnb private room reviews is measured as the natural logarithm of the total number of Airbnb private room reviews of the year prior to the transaction year. Livability is measured as the subjective livability rating of the year prior to the transaction year. All variables are measured at the neighbourhood-year level. The standard errors are clustered at the neighbourhood level. The standard errors are given between parentheses. The level of significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

Appendix H: Correlation matrices

Table 14
Correlation matrix for steps 1, 3 and 4

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
(1) Transaction price (*ln*)	1.000																						
(2) Reviews - All (*ln*)	0.417	1.000																					
(3) Reviews - Apartments (*ln*)	0.421	0.889	1.000																				
(4) Reviews - Private rooms (*ln*)	0.299	0.782	0.492	1.000																			
(5) Listings - All (*ln*)	0.393	0.935	0.913	0.658	1.000																		
(6) Liveability	0.609	0.330	0.408	0.099	0.371	1.000																	
(7) Surface area in m2 (*ln*)	0.625	-0.142	-0.198	0.003	-0.235	0.196	1.000																
(8) Building period - 1500-1905	0.411	0.559	0.546	0.361	0.498	0.331	0.015	1.000															
(9) Building period - 1906-1944	0.135	0.212	0.292	0.057	0.328	0.309	-0.260	-0.180	1.000														
(10) Building period - 1945-1970	-0.295	-0.302	-0.324	-0.148	-0.324	-0.352	-0.013	-0.257	-0.314	1.000													
(11) Building period - 1971-1990	-0.339	-0.261	-0.287	-0.133	-0.297	-0.198	-0.111	-0.136	-0.324	-0.106	1.000												
(12) Building period - 1991-2020	0.011	-0.247	-0.284	-0.136	-0.277	-0.176	0.362	-0.309	-0.440	-0.134	-0.233	1.000											
(13) Maintenance - Good	0.358	0.085	0.141	-0.025	0.103	0.159	0.246	0.142	0.004	-0.110	-0.286	0.185	1.000										
(14) Maintenance - Moderate	-0.284	-0.063	-0.107	0.032	-0.081	-0.147	-0.208	-0.096	-0.050	0.006	0.245	-0.062	-0.811	1.000									
(15) Maintenance - Bad	-0.086	-0.028	-0.042	-0.015	-0.025	-0.003	-0.039	-0.062	0.077	0.163	0.038	-0.186	-0.211	-0.402	1.000								
(15) Non-Western	-0.632	-0.391	-0.479	-0.135	-0.410	-0.778	-0.178	-0.442	-0.289	0.331	0.246	0.224	-0.193	0.172	0.016	1.000							
(16) Education - Low	-0.655	-0.480	-0.524	-0.237	-0.505	-0.697	-0.194	-0.434	-0.210	0.387	0.272	0.072	-0.237	0.177	0.076	0.823	1.000						
(17) Education - Mid	-0.589	-0.466	-0.526	-0.261	-0.530	-0.504	-0.099	-0.322	-0.279	0.269	0.359	0.080	-0.255	0.201	0.064	0.505	0.557	1.000					
(19) Education - High	0.710	0.535	0.591	0.278	0.580	0.701	0.178	0.441	0.266	-0.383	-0.344	-0.086	0.276	-0.211	-0.081	-0.787	-0.931	-0.821	1.000				
(18) Unemployment	-0.618	-0.260	-0.230	-0.191	-0.234	-0.529	-0.477	-0.294	0.001	0.206	0.266	-0.128	-0.256	0.211	0.047	0.668	0.755	0.357	-0.672	1.000			
(19) Households with children	-0.185	-0.465	-0.513	-0.232	-0.494	-0.271	0.392	-0.478	-0.172	0.139	0.038	0.433	-0.021	0.037	-0.028	0.446	0.486	0.330	-0.480	0.119	1.000		
(20) Number of cultural establishments (*ln*)	0.321	0.701	0.625	0.537	0.676	0.187	-0.099	0.575	0.107	-0.179	-0.246	-0.266	0.101	-0.080	-0.023	-0.306	-0.369	-0.352	0.410	-0.234	-0.471	1.000	
(21) Number of horeca establishments (*ln*)	0.365	0.782	0.786	0.532	0.837	0.396	-0.173	0.422	0.357	-0.282	-0.312	-0.268	0.107	-0.069	-0.052	-0.393	-0.457	-0.502	0.535	-0.197	-0.397	0.629	1.000

Table 15
Correlation matrix for step 2

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) Reviews - All (*ln*)	1.000																	
(2) Reviews - Apartments (*ln*)	0.889	1.000																
(3) Reviews - Private rooms (*ln*)	0.782	0.492	1.000															
(4) Listings - All (*ln*)	0.935	0.913	0.658	1.000														
(5) Liveability	0.330	0.408	0.099	0.371	1.000													
(6) Non-Western	-0.391	-0.479	-0.135	-0.410	-0.778	1.000												
(7) Household - One adult	0.428	0.477	0.209	0.459	0.126	-0.220	1.000											
(8) Household - One adult with child(ren)	-0.426	-0.466	-0.217	-0.440	-0.442	0.707	-0.465	1.000										
(9) Household - More than one adult without child(ren)	0.043	0.052	0.008	0.036	0.368	-0.555	-0.239	-0.492	1.000									
(10) Household - More than one adult with child(ren)	-0.388	-0.430	-0.192	-0.418	-0.138	0.237	-0.932	0.390	0.013	1.000								
(11) Education - Low	-0.480	-0.524	-0.237	-0.505	-0.697	0.823	-0.284	0.722	-0.474	0.280	1.000							
(12) Education - Mid	-0.466	-0.526	-0.261	-0.530	-0.504	0.505	-0.198	0.456	-0.301	0.205	0.557	1.000						
(13) Education - High	0.535	0.591	0.278	0.580	0.701	-0.787	0.283	-0.697	0.457	-0.283	-0.931	-0.821	1.000					
(14) Duration of residence (years)	-0.200	-0.179	-0.138	-0.220	0.125	-0.083	-0.144	0.203	0.061	0.081	0.226	0.290	-0.282	1.000				
(15) Physical environment rating	-0.491	-0.525	-0.240	-0.602	-0.240	0.140	-0.482	0.226	0.121	0.456	0.220	0.338	-0.299	0.075	1.000			
(16) Number of services (*ln*)	0.696	0.653	0.531	0.744	0.330	-0.235	0.239	-0.188	-0.044	-0.210	-0.355	-0.395	0.418	-0.134	-0.441	1.000		
(17) Number of cultural establishments (*ln*)	0.701	0.625	0.537	0.676	0.187	-0.306	0.420	-0.411	0.081	-0.409	-0.369	-0.352	0.410	-0.166	-0.347	0.620	1.000	
(18) Number of horeca establishments (*ln*)	0.782	0.786	0.532	0.837	0.396	-0.393	0.376	-0.324	0.016	-0.349	-0.457	-0.502	0.535	-0.125	-0.530	0.889	0.629	1.000

Appendix I: The number of reviews per neighborhood (map)

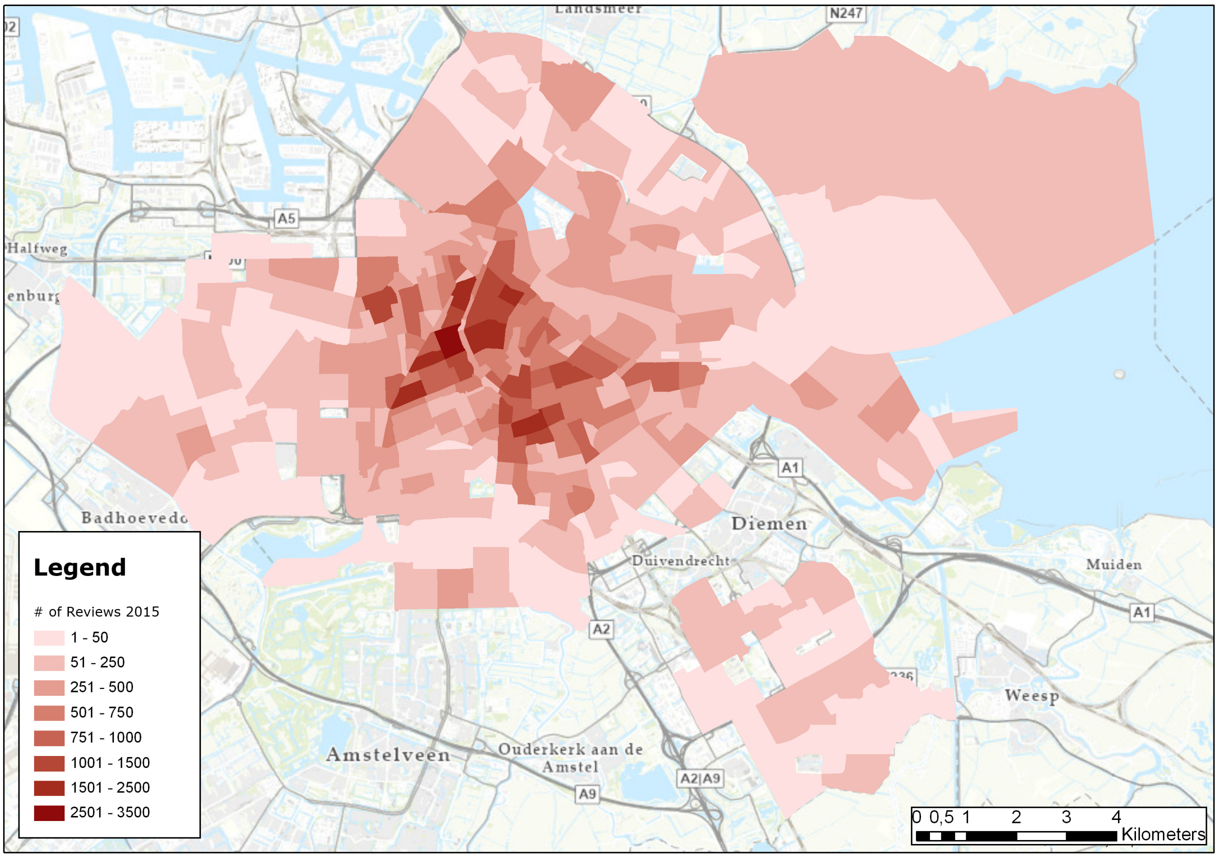

Figure 3*: The number of reviews per neighborhood of the municipality of Amsterdam in 2015*

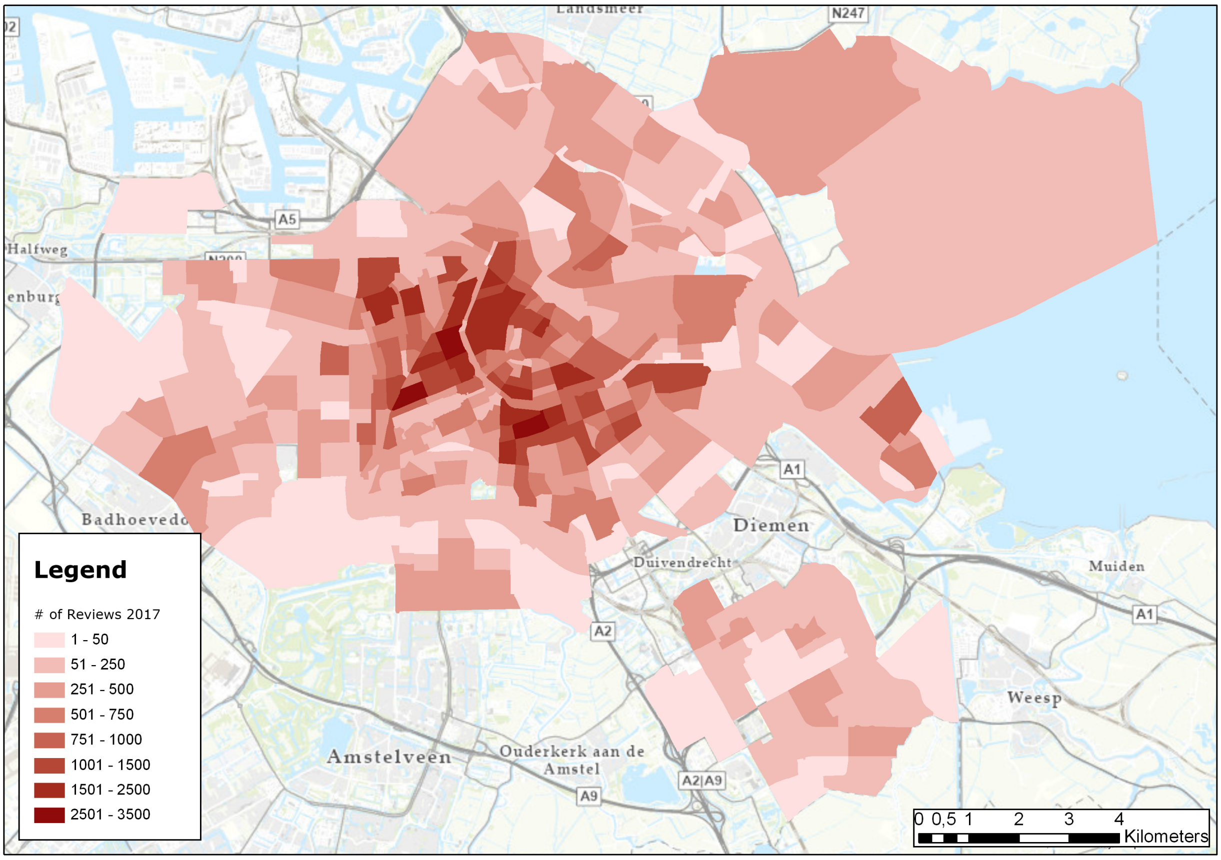

***Figure 4**: The number of reviews per neighborhood of the municipality of Amsterdam in 2017*

Appendix J: Airbnb

Airbnb started out in 2008 as a website to facilitate bookings for consumers who wished to rent out unused or underused space, such as an air mattress, a couch or a spare room. Airbnb is a so called short-term rental company. Also known as peer-to-peer (P2P) rental, short term rental is defined as an individual or household renting (a portion of) a private home, apartment or other private space to another individual or household for a period less than 30 days (Jordan and Moore, 2018). This is different from the traditional form of tourism accommodation which involves business-to-consumer (B2C) transactions, such as hotels. Over the years, Airbnb's popularity skyrocketed and grew to be the biggest short-term rental broker of the world (Gutiérrez et al., 2017). As of today, Airbnb facilitated more than 800 million guest arrivals worldwide, lists more than seven million listings in over 220 countries and 100.000 cities and accommodates more than two million people across the world every day (Airbnb, 2020a). It thereby surpassed all mayor and well-established hotel chains, such as Marriot, Hilton and InterContinental, in number of beds offered and in market valuation (Oskam and Boswijk, 2016). While Airbnb is not the only short-term rental company on the Dutch market, it is certainly the market leader in this particular domain (Guttentag, 2015; Oskam and Boswijk, 2016).

One might ask how Airbnb became the biggest short-term rental broker of the world. There are multiple explanations to the explosive growth of Airbnb.

Firstly, unlike conventional hotels, Airbnb does not own or manage any property itself. It merely acts as a broker between property owners wishing to rent out space on the short-term rental market and consumers or business travelers looking for accommodation (Kenny and Zysman, 2016). As a result, Airbnb does not have to deal with cleaning rooms, having a reception or doing maintenance on the properties like other hotels have to.

Secondly, before the inception of Airbnb and other short-term rental brokers, consumer-to-consumer accommodation was limited, because it was difficult for hosts to advertise their accommodation to consumers and business travelers looking for accommodation. Airbnb overcame this obstacle by its use of the internet and Web 2.0 technologies. By using the internet, hosts could easily reach millions of potential renters and consumers or business travelers looking for a place to sleep have a variety of options to choose from on the platform. This makes Airbnb an attractive platform for both hosts and renters (Guttentag, 2015; Habibi, Davidson and Laroche, 2017).

Thirdly, every home owner could be a potential Airbnb landlord and thus a large portion of the housing stock could have the potential to become an Airbnb listing. Home owners wishing to rent out (a spare room in) their residence could easily create a listing on the Airbnb website. Home owners wishing to rent out an entire house, which was previously occupied by a long-term tenant would only need to remove the existing tenant before he/she could list the property on the Airbnb platform (Wachsmuth and Weisler, 2018).

Lastly, with platform like Airbnb, growth leads to increasing returns to scale. When more consumers make use of the platform and more listings are available on the platform, it is easier to find the right match between the two. The platform then becomes more valuable and users pay more for access to a larger network (Eisenmann, Parker and Van Alstyne, 2006).

Together, these traits make Airbnb's business model unique. It could be said that Airbnb's business model was truly disruptive for the short-term rental industry at the time of its inception in 2008 (Christensen and Raynor, 2003). According to disruptive innovation theory, products and services that offer alternative benefits than the traditional products and services on the market can transform that market and capture most of the market share (Guttentag, 2015). Airbnb's business model was a first of its kind and had a first movers' advantage over its competitors, which allowed it to become the largest short-term rental broker of the world.

Disruptive technologies often outpace applicable regulations, resulting in concerns such as general legality or taxation (Carrns, 2013; Song, 2011; Wolverton, 2002). Therefore, in many cities around the world, short-term rental is legally restricted (Dann et al., 2019). In Paris, for example, rentals of less than 12 months are prohibited without a license (Huet, 2021). However, in the Netherlands, several municipalities have embraced short-term rentals. The goal of these municipalities is to promote tourism, while tourism can bring economic and social benefits to a city (Bahceli, 2015; Kok, 2015). One of these cities which embraced short-term rentals is Amsterdam. During the financial and housing crisis between 2007 and 2010, the municipality thought that allowing short-term rentals would help home owners to pay for their mortgages. The municipality also wished to increase visitor numbers and spread tourist spending over more neighborhoods so that more residents could benefit of the increasing number of tourists in their city (Oskam and Boswijk, 2016). Thus, the municipality of Amsterdam did not want to be too stringent by prohibiting all short-term rental activity in their city. Instead of prohibiting short-term rental activity, the municipality of Amsterdam and Airbnb sat down at the table and discussed what would be best for all parties involved. In the end, Amsterdam passed "Airbnb friendly legislation" (van de Glind and van Sprang, 2015). They agreed that from the 1st of January, 2017, entire homes could only be rented for a maximum of 60 days per year if the home-owner did not have a license (Dann et al., 2019).

In the early years of Airbnb, things worked out. However, due to the steep tourism growth in general and the popularity of short-term rentals in particular, many investors saw the potential to earn great amounts of money by transforming long-term rentals to short-term rentals. They started building a portfolio of Airbnb properties in the most popular neighborhoods, driving up real estate values and rental prices (Oskam and Boswijk, 2016). Due to the rising residential real estate values and the upward pressure on livability in some neighborhoods in Amsterdam, the municipality decided to intervene. The current situation was not sustainable in the long run. Because the negative effects of short-term rentals became more visible, the municipality eventually decreased the number of days entire homes without a license could be rented to 30 days per year (Municipality of Amsterdam, 2020a).

Appendix K: STATA-code


```
* //The effect of Airbnb on residential real estate values and liveability in Amsterdam
* //From individual NVM listings to aggregated neighbourhood data
* //Master thesis Ukyo Morpey, S2884542

* //Change directory to folder with data files
cd "C:\Users\ukyo2\Documents\Real Estate Studies\Jaar 2\MT\STATA"

* //Creating a log file to store output
log using "Thesis - log.txt", replace

clear all
set more off
set maxvar 32767

* //dir

* //Reading Excel files
import excel using "NVM.xlsx",  firstrow

* //Drop observations
drop if TYPE == 2
drop if TYPE == 3
drop if TYPE == 8

* //Generate new variables for house type
gen DETACHED = 0
replace DETACHED = 1 if inlist(TYPE, 9, 10, 11)
gen APARTMENT = 0
replace APARTMENT = 1 if inlist(TYPE, 21, 22, 23, 24, 25, 27)
gen TERRACED = 0
replace TERRACED = 1 if inlist(TYPE, 5, 6, 7)

* //Generate new variables (combine certain categories)
gen PRICEM2 = PRICE/SQUARE_METER

clonevar GARDEN_YN = GARDEN
replace GARDEN_YN = 1 if GARDEN_YN > 0

clonevar PARKING_YN = PARKING
replace PARKING_YN = 1 if PARKING_YN > 0

gen ONBU_BAD = 0
replace ONBU_BAD = 1 if ONBU < 6

gen ONBU_GOOD = 0
replace ONBU_GOOD = 1 if ONBU >= 8

gen ONBU_MODERATE = 0
replace ONBU_MODERATE = 1 if ONBU_GOOD == 0
replace ONBU_MODERATE = 0 if ONBU_BAD == 1

gen ONBI_BAD = 0
replace ONBI_BAD = 1 if ONBI < 6

gen ONBI_GOOD = 0
replace ONBI_GOOD = 1 if ONBI >= 8

gen ONBI_MODERATE = 0
replace ONBI_MODERATE = 1 if ONBI_GOOD == 0
replace ONBI_MODERATE = 0 if ONBI_BAD == 1

* //Generate new variables for natural log of numerical variables
gen ln_PRICE = log(PRICE)
gen ln_PRICEM2 = log(PRICEM2)
gen ln_SQUARE_METER = log(SQUARE_METER)
gen ln_VOLUME = log(VOLUME)
gen ln_ROOMS = log(ROOMS)
gen ln_GARDEN = log(GARDEN)
```

```
* //Create macro's for dependent independent and control variables
local num_variables ln_PRICE ln_PRICEM2 ln_SQUARE_METER ln_VOLUME ln_ROOMS ln_GARDEN PRICE PRICEM2 SQUARE_METER VOLUME ROOMS GARDEN
local str_variables YEAR YEAR_MONTH YEAR_QUARTER BUILDING_PERIOD PARKING PARKING_YN MONUMENT MONUMENTAL  GARDEN_YN LIFT ISOL HEATING

* //Summarizing categorical variable
foreach x of local str_variables {
tab `x'
}

* // Generate dummies and create local macro
foreach x of local str_variables {
tab `x', gen (`x'dum)
}

* //Generate new variables for building period
gen BUILDING_PERIOD_NEW_1 = BUILDING_PERIODdum1
gen BUILDING_PERIOD_NEW_2 = BUILDING_PERIODdum2 + BUILDING_PERIODdum3
gen BUILDING_PERIOD_NEW_3 = BUILDING_PERIODdum4 + BUILDING_PERIODdum5
gen BUILDING_PERIOD_NEW_4 = BUILDING_PERIODdum6 + BUILDING_PERIODdum7
gen BUILDING_PERIOD_NEW_5 = BUILDING_PERIODdum8 + BUILDING_PERIODdum9

* //Descriptive statistics to excel
putexcel set descriptive_statistics_real_estate.xlsx, replace
sort YEAR
tabstat PRICE SQUARE_METER BUILDING_PERIOD_NEW* ONBI_GOOD ONBI_MODERATE ONBI_BAD YEAR_QUARTERdum*, stat(n mean median sd min max p25 p75) by(YEAR) save
return list
putexcel B2= matrix(r(Stat1)'), names nformat(number_d2)
putexcel B27= matrix(r(Stat2)'), names nformat(number_d2)
putexcel B52= matrix(r(Stat3)'), names nformat(number_d2)
putexcel B77= matrix(r(StatTotal)'), names nformat(number_d2)

* //Create mean variables
sort NEIGHBOURHOOD_YEAR

foreach x of local num_variables {
by NEIGHBOURHOOD_YEAR: egen mean_`x' = mean(`x')
}

foreach x of varlist YEARdum* YEAR_MONTHdum* YEAR_QUARTERdum* BUILDING_PERIODdum* PARKING_YNdum* MONUMENTdum* MONUMENTALdum*  GARDEN_YNdum* LIFTdum* ISOLdum* HEATINGdum* DETACHED APARTMENT TERRACED ONBI_GOOD ONBI_MODERATE ONBI_BAD ONBU_GOOD ONBU_MODERATE ONBU_BAD {
tab `x'
by NEIGHBOURHOOD_YEAR: egen mean_`x' = mean(`x')
}

* //save to new dataset
save NVM_NEIGHBOURHOOD.dta, replace

log close
```

```
* //The effect of Airbnb activity on residential real estate values and livability: The case for the Netherlands
* //Master thesis Ukyo Morpey, S2884542

* //Change directory to folder with data files
cd "C:\Users\ukyo2\Documents\Real Estate Studies\Jaar 2\MT\STATA"

* //Creating a log file to store output
log using "Thesis - log.txt", replace

clear all
set more off
set maxvar 32767

* //dir

* //Reading Excel files and merge datasets
import excel using "NVM_NEIGHBOURHOOD.xlsx",  firstrow
joinby NEIGHBOURHOOD_YEAR using "AIRBNB.dta"
save AIRBNB_NVM.dta, replace

clear all
set more off

import excel using "LIVEABILITY AND CONTROLS.xlsx",  firstrow
joinby NEIGHBOURHOOD_YEAR using "AIRBNB_NVM.dta"

* //Drop variables with missing values
drop if missing(LBUURT_R)
drop if L_APT < 1
drop if L_PVT < 1

* //Generate new variables for natural log of independent variables
gen ln_R_ALL = log(R_ALL)
gen ln_R_APT = log(R_APT)
gen ln_R_PVT = log(R_PVT)
gen ln_L_ALL = log(L_ALL)

* //Generate new variables for locational variables
gen ln_BHVEST_VOORZ = log(BHVEST_VOORZ)
gen ln_BHVEST_CULT = log(BHVEST_CULT)
gen ln_BHVEST_HORECA = log(BHVEST_HORECA)

* //Generate new variables for building period
gen BUILDING_PERIOD_NEW_1 = BUILDING_PERIODdum1
gen BUILDING_PERIOD_NEW_2 = BUILDING_PERIODdum2 + BUILDING_PERIODdum3
gen BUILDING_PERIOD_NEW_3 = BUILDING_PERIODdum4 + BUILDING_PERIODdum5
gen BUILDING_PERIOD_NEW_4 = BUILDING_PERIODdum6 + BUILDING_PERIODdum7
gen BUILDING_PERIOD_NEW_5 = BUILDING_PERIODdum8 + BUILDING_PERIODdum9

* //Create macro's for dependent independent and control variables
local dependent ln_PRICE

local independent1 ln_R_ALL
local independent2 ln_L_ALL
local independent3 ln_R_APT ln_R_PVT

local mediator LBUURT_R

local num_controls ln_SQUARE_METER
local str_controls BUILDING_PERIOD_NEW_1-BUILDING_PERIOD_NEW_3 BUILDING_PERIOD_NEW_5 ONBI_GOOD ONBI_MODERATE

local locational_controls BEVNW_P BEVOPLLAAG_P BEVOPLMID_P PREGWERKL_P BEVHHMKIND_P

local mediator_controls BEVNW_P BEVALLEENHH_P BEVEENOUDERHH_P BEVPAARZKINDHH_P BEVPAARMKINDHH_P BEVOPLLAAG_P BEVOPLMID_P BEVWOONDUUR RLBFYS ln_BHVEST_VOORZ

```

```
local quarter_fe YEAR_QUARTER*
local year_fe YEARdum*

local hausman ln_BHVEST_HORECA ln_BHVEST_CULT

* //Exclude outliers for numerical variables
centile(`dependent'), centile(0.5, 99.5)
drop if ( `dependent' < r(c_1) | `dependent' > r(c_2) )

centile(`independent1'), centile(0.5, 99.5)
drop if ( `independent1' < r(c_1) | `independent1' > r(c_2) )

centile(`mediator'), centile(0.5, 99.5)
drop if ( `mediator' < r(c_1) | `mediator' > r(c_2) )

* //Correlation matrices
pwcorr `dependent' `independent1' `independent2' `independent3' `mediator' `num_controls' `str_controls' `locational_controls' `hausman'
pwcorr `independent1' `independent2' `independent3' `mediator' `mediator_controls' `hausman'

* //Covariance matrices
corr `dependent' `independent1' `independent2' `independent3' `mediator' `num_controls' `str_controls' `locational_controls', cov
corr `independent1' `independent2' `independent3' `mediator' `mediator_controls', cov

* //Generate histogram
set scheme s1color, permanently
sum `dependent', detail
hist `dependent', fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("`dependent'") normal
graph save `dependent', replace

sum `independent1', detail
hist `independent1', fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("`independent1'") normal
graph save `independent1', replace

sum `independent2', detail
foreach x of local independent2 {
hist `x', fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("`x'") normal
graph save `x', replace
}

sum `independent3', detail
foreach x of local independent3 {
hist `x', fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("`x'") normal
graph save `x', replace
}

sum `mediator', detail
hist `mediator', fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("`mediator'") normal
graph save `mediator', replace

sum `num_controls', detail
foreach x of local num_controls {
hist `x', fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("`x'") normal
graph save `x', replace
}

sum `str_controls', detail
foreach x of varlist ONBI_GOOD ONBI_MODERATE {
hist `x', fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("`x'") normal
graph save `x', replace
}

sum `locational_controls', detail
foreach x of local locational_controls {
```

```
hist `x', fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("`x'") normal
graph save `x', replace
}

sum `mediator_controls', detail
foreach x of local mediator_controls {
hist `x', fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("`x'") normal
graph save `x', replace
}

sum `hausman', detail
foreach x of local hausman {
hist `x', fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("`x'") normal
graph save `x', replace
}

* //Regressions Step 1a
quietly reg `dependent' `independent1', cluster(NEIGHBOURHOOD)
eststo m1, title(Model 1)
quietly reg `dependent' `independent1' `num_controls' `str_controls', cluster(NEIGHBOURHOOD)
eststo m2, title(Model 2)
quietly reg `dependent' `independent1' `num_controls' `str_controls' `locational_controls', cluster(NEIGHBOURHOOD)
eststo m3, title(Model 3)
quietly reg `dependent' `independent1' `num_controls' `str_controls' `locational_controls' `quarter_fe', cluster(NEIGHBOURHOOD)
eststo m4, title(Model 4)

* //Regressions Step 1b
quietly reg `dependent' `independent2', cluster(NEIGHBOURHOOD)
eststo m5, title(Model 5)
quietly reg `dependent' `independent2' `num_controls' `str_controls', cluster(NEIGHBOURHOOD)
eststo m6, title(Model 6)
quietly reg `dependent' `independent2' `num_controls' `str_controls' `locational_controls', cluster(NEIGHBOURHOOD)
eststo m7, title(Model 7)
quietly reg `dependent' `independent2' `num_controls' `str_controls' `locational_controls' `quarter_fe', cluster(NEIGHBOURHOOD)
eststo m8, title(Model 8)

* //Regressions Step 1c
quietly reg `dependent' `independent3', cluster(NEIGHBOURHOOD)
eststo m9, title(Model 9)
quietly reg `dependent' `independent3' `num_controls' `str_controls', cluster(NEIGHBOURHOOD)
eststo m10, title(Model 10)
quietly reg `dependent' `independent3' `num_controls' `str_controls' `locational_controls', cluster(NEIGHBOURHOOD)
eststo m11, title(Model 11)
quietly reg `dependent' `independent3' `num_controls' `str_controls' `locational_controls' `quarter_fe', cluster(NEIGHBOURHOOD)
eststo m12, title(Model 12)

* //Regressions Step 2a
quietly reg `mediator' `independent1'
eststo m13, title(Model 13)
quietly reg `mediator' `independent1' `mediator_controls'
eststo m14, title(Model 14)
quietly reg `mediator' `independent1' `mediator_controls' `year_fe'
eststo m15, title(Model 15)

* //Regressions Step 2b
quietly reg `mediator' `independent2'
eststo m16, title(Model 16)
quietly reg `mediator' `independent2' `mediator_controls'
eststo m17, title(Model 17)
quietly reg `mediator' `independent2' `mediator_controls' `year_fe'
eststo m18, title(Model 18)
```

```
* //Regressions Step 2c
quietly reg `mediator' `independent3'
eststo m19, title(Model 19)
quietly reg `mediator' `independent3' `mediator_controls'
eststo m20, title(Model 20)
quietly reg `mediator' `independent3' `mediator_controls' `year_fe'
eststo m21, title(Model 21)

* //Regressions Step 3
quietly reg `dependent' `mediator', cluster(NEIGHBOURHOOD)
eststo m22, title(Model 22)
quietly reg `dependent' `mediator' `num_controls' `str_controls', cluster(NEIGHBOURHOOD)
eststo m23, title(Model 23)
quietly reg `dependent' `mediator' `num_controls' `str_controls' `locational_controls', cluster(NEIGHBOURHOOD)
eststo m24, title(Model 24)
quietly reg `dependent' `mediator' `num_controls' `str_controls' `locational_controls' `quarter_fe', cluster(NEIGHBOURHOOD)
eststo m25, title(Model 25)

* //Regressions Step 4a
quietly reg `dependent' `independent1' `mediator', cluster(NEIGHBOURHOOD)
eststo m26, title(Model 26)
quietly reg `dependent' `independent1' `mediator' `num_controls' `str_controls', cluster(NEIGHBOURHOOD)
eststo m27, title(Model 27)
quietly reg `dependent' `independent1' `mediator' `num_controls' `str_controls' `locational_controls', cluster(NEIGHBOURHOOD)
eststo m28, title(Model 28)
quietly reg `dependent' `independent1' `mediator' `num_controls' `str_controls' `locational_controls' `quarter_fe', cluster(NEIGHBOURHOOD)
eststo m29, title(Model 29)

* //Regressions Step 4b
quietly reg `dependent' `independent2' `mediator', cluster(NEIGHBOURHOOD)
eststo m30, title(Model 30)
quietly reg `dependent' `independent2' `mediator' `num_controls' `str_controls', cluster(NEIGHBOURHOOD)
eststo m31, title(Model 31)
quietly reg `dependent' `independent2' `mediator' `num_controls' `str_controls' `locational_controls', cluster(NEIGHBOURHOOD)
eststo m32, title(Model 32)
quietly reg `dependent' `independent2' `mediator' `num_controls' `str_controls' `locational_controls' `quarter_fe', cluster(NEIGHBOURHOOD)
eststo m33, title(Model 33)

* //Regressions Step 4c
quietly reg `dependent' `independent3' `mediator', cluster(NEIGHBOURHOOD)
eststo m34, title(Model 34)
quietly reg `dependent' `independent3' `mediator' `num_controls' `str_controls', cluster(NEIGHBOURHOOD)
eststo m35, title(Model 35)
quietly reg `dependent' `independent3' `mediator' `num_controls' `str_controls' `locational_controls', cluster(NEIGHBOURHOOD)
eststo m36, title(Model 36)
quietly reg `dependent' `independent3' `mediator' `num_controls' `str_controls' `locational_controls' `quarter_fe', cluster(NEIGHBOURHOOD)
eststo m37, title(Model 37)

* //Output step 1a
estout m1 m2 m3 m4, cells(b(star fmt(%9.3f)) se(par)) ///
           starlevel(* 0.1 ** 0.05 *** 0.01) stats(r2_a N, fmt(%9.3f %9.0g) labels(R-squared)) ///
           legend drop(YEAR*) nobaselevel

* //Output step 1b
estout m5 m6 m7 m8, cells(b(star fmt(%9.3f)) se(par))
```

```
///
            starlevel(* 0.1 ** 0.05 *** 0.01) stats(r2_a N, fmt(%9.3f %9.0g) labels(R-squared)) ///
            legend drop(YEAR*) nobaselevel

* //Output step 1c
estout m9 m10 m11 m12, cells(b(star fmt(%9.3f)) se(par)) ///
            starlevel(* 0.1 ** 0.05 *** 0.01) stats(r2_a N, fmt(%9.3f %9.0g) labels(R-squared)) ///
            legend drop(YEAR*) nobaselevel

* //Output step 2a
estout m13 m14 m15, cells(b(star fmt(%9.3f)) se(par)) ///
            starlevel(* 0.1 ** 0.05 *** 0.01) stats(r2_a N, fmt(%9.3f %9.0g) labels(R-squared)) ///
            legend drop(YEAR*) nobaselevel

* //Output step 2b
estout m16 m17 m18, cells(b(star fmt(%9.3f)) se(par)) ///
            starlevel(* 0.1 ** 0.05 *** 0.01) stats(r2_a N, fmt(%9.3f %9.0g) labels(R-squared)) ///
            legend drop(YEAR*) nobaselevel

* //Output step 2c
estout m19 m20 m21, cells(b(star fmt(%9.3f)) se(par)) ///
            starlevel(* 0.1 ** 0.05 *** 0.01) stats(r2_a N, fmt(%9.3f %9.0g) labels(R-squared)) ///
            legend drop(YEAR*) nobaselevel

* //Output step 3
estout m22 m23 m24 m25, cells(b(star fmt(%9.3f)) se(par)) ///
            starlevel(* 0.1 ** 0.05 *** 0.01) stats(r2_a N, fmt(%9.3f %9.0g) labels(R-squared)) ///
            legend drop(YEAR*) nobaselevel

* //Output step 4a
estout m26 m27 m28 m29, cells(b(star fmt(%9.3f)) se(par)) ///
            starlevel(* 0.1 ** 0.05 *** 0.01) stats(r2_a N, fmt(%9.3f %9.0g) labels(R-squared)) ///
            legend drop(YEAR*) nobaselevel

* //Output step 4b
estout m30 m31 m32 m33, cells(b(star fmt(%9.3f)) se(par)) ///
            starlevel(* 0.1 ** 0.05 *** 0.01) stats(r2_a N, fmt(%9.3f %9.0g) labels(R-squared)) ///
            legend drop(YEAR*) nobaselevel

* //Output step 4c
estout m34 m35 m36 m37, cells(b(star fmt(%9.3f)) se(par)) ///
            starlevel(* 0.1 ** 0.05 *** 0.01) stats(r2_a N, fmt(%9.3f %9.0g) labels(R-squared)) ///
            legend drop(YEAR*) nobaselevel

* //Regression results to excel
esttab using regression_results.csv, replace cells(b(star fmt(%9.3f)) se(par)) ///
            starlevel(* 0.1 ** 0.05 *** 0.01) stats(r2_a N, fmt(%9.3f %9.0g) labels(R-squared)) ///
            legend drop(YEAR*) nobaselevel

```

```
* //Post estimation tests step 1A
* //Residuals vs. fitted values plot
quietly reg `dependent' `independent1' `num_controls' `str_controls' `locational_controls' `quarter_fe'
rvfplot, yline(0) title("Residual vs. Fitted Plot")
graph save "rvfplot_step1A", replace

* //Qnormal plot residuals
predict r_step1A, residuals
qnorm r_step1A, title("Q-normal Plot: Residuals")
graph save "qnormal_step1A", replace

* //Histogram residuals
hist r_step1A, fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("Histogram: Residuals") normal
graph save "histogram residuals_step1A", replace

* //Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
estat hettest

* //White's test
estat imtest, white

* //Omitted variables test RESET
ovtest

* //VIF
vif

* //Skewness and kurtosis test residuals
sktest r_step1A

* //Durban Wu Hausman test
reg `independent1' `hausman'
predict r_step1A_hausman, res
reg `dependent' `independent1' `num_controls' `str_controls' `locational_controls' `quarter_fe' r_step1A_hausman
test r_step1A_hausman

ivregress 2sls `dependent' `num_controls' `str_controls' `locational_controls' `quarter_fe' (`independent1' = `hausman')

eststo m38, title(Model 38)

estat firststage

estat overid

* //Post estimation tests step 1B
* //Residuals vs. fitted values plot
quietly reg `dependent' `independent2' `num_controls' `str_controls' `locational_controls' `quarter_fe'
rvfplot, yline(0) title("Residual vs. Fitted Plot")
graph save "rvfplot_step1B", replace

* //Qnormal plot residuals
predict r_step1B, residuals
qnorm r_step1B, title("Q-normal Plot: Residuals")
graph save "qnormal_step1B", replace

* //Histogram residuals
hist r_step1B, fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("Histogram: Residuals") normal
graph save "histogram residuals_step1B", replace

* //Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
estat hettest
```

```
* //White's test
estat imtest, white

* //Omitted variables test RESET
ovtest

* //VIF
vif

* //Skewness and kurtosis test residuals
sktest r_step1B

* //Durban Wu Hausman test
reg `independent2' `hausman'
predict r_step1B_hausman, res
reg `dependent' `independent2' `num_controls' `str_controls' `locational_controls' `quarter_fe'
r_step1B_hausman
test r_step1B_hausman

* //Post estimation tests step 1C
* //Residuals vs. fitted values plot
quietly reg `dependent' `independent3' `num_controls' `str_controls' `locational_controls'
`quarter_fe'
rvfplot, yline(0) title("Residual vs. Fitted Plot")
graph save "rvfplot_step1C", replace

* //Qnormal plot residuals
predict r_step1C, residuals
qnorm r_step1C, title("Q-normal Plot: Residuals")
graph save "qnormal_step1C", replace

* //Histogram residuals
hist r_step1C, fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("Histogram:
Residuals") normal
graph save "histogram residuals_step1C", replace

* //Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
estat hettest

* //White's test
estat imtest, white

* //Omitted variables test RESET
ovtest

* //VIF
vif

* //Skewness and kurtosis test residuals
sktest r_step1C

* //Durban Wu Hausman test
reg `independent3' `hausman'
predict r_step1C_hausman, res
reg `dependent' `independent3' `num_controls' `str_controls' `locational_controls' `quarter_fe'
r_step1C_hausman
test r_step1C_hausman

* //Post estimation tests step 2A
* //Residuals vs. fitted values plot
quietly reg `mediator' `independent1' `mediator_controls' `quarter_fe'
rvfplot, yline(0) title("Residual vs. Fitted Plot")
graph save "rvfplot_step2A", replace

* //Qnormal plot residuals
predict r_step2A, residuals
qnorm r_step2A, title("Q-normal Plot: Residuals")
graph save "qnormal_step2A", replace
```

```
* //Histogram residuals
hist r_step2A, fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("Histogram:
Residuals") normal
graph save "histogram residuals_step2A", replace

* //Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
estat hettest

* //White's test
estat imtest, white

* //Omitted variables test RESET
ovtest

* //VIF
vif

* //Skewness and kurtosis test residuals
sktest r_step2A

* //Durban Wu Hausman test
reg `independent1' `hausman'
predict r_step2A_hausman, res
reg `mediator' `independent1' `mediator_controls' `year_fe' r_step2A_hausman
test r_step2A_hausman

ivregress 2sls `mediator' `mediator_controls' `year_fe' (`independent1' = `hausman')

eststo m39, title(Model 39)

estat firststage

estat overid

* //Post estimation tests step 2B
* //Residuals vs. fitted values plot
quietly reg `mediator' `independent2' `mediator_controls' `quarter_fe'
rvfplot, yline(0) title("Residual vs. Fitted Plot")
graph save "rvfplot_step2B", replace

* //Qnormal plot residuals
predict r_step2B, residuals
qnorm r_step2B, title("Q-normal Plot: Residuals")
graph save "qnormal_step2B", replace

* //Histogram residuals
hist r_step2B, fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("Histogram:
Residuals") normal
graph save "histogram residuals_step2B", replace

* //Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
estat hettest

* //White's test
estat imtest, white

* //Omitted variables test RESET
ovtest

* //VIF
vif

* //Skewness and kurtosis test residuals
sktest r_step2B

* //Durban Wu Hausman test
reg `independent2' `hausman'
```

```
predict r_step2B_hausman, res
reg `mediator' `independent2' `mediator_controls' `quarter_fe' r_step2B_hausman
test r_step2B_hausman

* //Post estimation tests step 2C
* //Residuals vs. fitted values plot
quietly reg `mediator' `independent3' `mediator_controls' `quarter_fe'
rvfplot, yline(0) title("Residual vs. Fitted Plot")
graph save "rvfplot_step2C", replace

* //Qnormal plot residuals
predict r_step2C, residuals
qnorm r_step2C, title("Q-normal Plot: Residuals")
graph save "qnormal_step2C", replace

* //Histogram residuals
hist r_step2C, fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("Histogram:
Residuals") normal
graph save "histogram residuals_step2C", replace

* //Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
estat hettest

* //White's test
estat imtest, white

* //Omitted variables test RESET
ovtest

* //VIF
vif

* //Skewness and kurtosis test residuals
sktest r_step2C

* //Durban Wu Hausman test
reg `independent3' `hausman'
predict r_step2C_hausman, res
reg `mediator' `independent3' `mediator_controls' `quarter_fe' r_step2C_hausman
test r_step2C_hausman

* //Post estimation tests step 3
* //Residuals vs. fitted values plot
quietly reg `dependent' `mediator' `num_controls' `str_controls' `locational_controls' `quarter_fe'
rvfplot, yline(0) title("Residual vs. Fitted Plot")
graph save "rvfplot_step3", replace

* //Qnormal plot residuals
predict r_step3, residuals
qnorm r_step3, title("Q-normal Plot: Residuals")
graph save "qnormal_step3", replace

* //Histogram residuals
hist r_step3, fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("Histogram:
Residuals") normal
graph save "histogram residuals_step3", replace

* //Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
estat hettest

* //White's test
estat imtest, white

* //Omitted variables test RESET
ovtest

* //VIF
vif
```

```
* //Skewness and kurtosis test residuals
sktest r_step3

* //Post estimation tests step 4A
* //Residuals vs. fitted values plot
quietly reg `dependent' `independent1' `mediator' `num_controls' `str_controls' `locational_controls' `quarter_fe'
rvfplot, yline(0) title("Residual vs. Fitted Plot")
graph save "rvfplot_step4A", replace

* //Qnormal plot residuals
predict r_step4A, residuals
qnorm r_step4A, title("Q-normal Plot: Residuals")
graph save "qnormal_step4A", replace

* //Histogram residuals
hist r_step4A, fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("Histogram: Residuals") normal
graph save "histogram residuals_step4A", replace

* //Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
estat hettest

* //White's test
estat imtest, white

* //Omitted variables test RESET
ovtest

* //VIF
vif

* //Skewness and kurtosis test residuals
sktest r_step4A

* //Durban Wu Hausman test
reg `independent1' `hausman'
predict r_step4A_hausman, res
reg `dependent' `independent1' `mediator' `num_controls' `str_controls' `locational_controls' `quarter_fe' r_step4A_hausman
test r_step4A_hausman

ivregress 2sls `dependent' `mediator' `num_controls' `str_controls' `locational_controls' `quarter_fe' (`independent1' = `hausman')

eststo m40, title(Model 40)

*esttab m38 m39 m40 using regression_results_IV.csv, replace cells(b(star fmt(%9.3f)) se(par))                          ///
*           starlevel(* 0.1 ** 0.05 *** 0.01) stats(r2_a N, fmt(%9.3f %9.0g) labels(R-squared))         ///
*           legend drop(YEAR*) nobaselevel

estat firststage

estat overid

* //Post estimation tests step 4B
* //Residuals vs. fitted values plot
quietly reg `dependent' `independent2' `mediator' `num_controls' `str_controls' `locational_controls' `quarter_fe'
rvfplot, yline(0) title("Residual vs. Fitted Plot")
graph save "rvfplot_step4B", replace

* //Qnormal plot residuals
predict r_step4B, residuals
qnorm r_step4B, title("Q-normal Plot: Residuals")
```

```
graph save "qnormal_step4B", replace

* //Histogram residuals
hist r_step4B, fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("Histogram:
Residuals") normal
graph save "histogram residuals_step4B", replace

* //Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
estat hettest

* //White's test
estat imtest, white

* //Omitted variables test RESET
ovtest

* //VIF
vif

* //Skewness and kurtosis test residuals
sktest r_step4B

* //Durban Wu Hausman test
reg `independent2' `hausman'
predict r_step4B_hausman, res
reg `dependent' `independent2' `mediator' `num_controls' `str_controls' `locational_controls'
`quarter_fe' r_step4B_hausman
test r_step4B_hausman

* //Post estimation tests step 4C
* //Residuals vs. fitted values plot
quietly reg `dependent' `independent3' `mediator' `num_controls' `str_controls'
`locational_controls' `quarter_fe'
rvfplot, yline(0) title("Residual vs. Fitted Plot")
graph save "rvfplot_step4C", replace

* //Qnormal plot residuals
predict r_step4C, residuals
qnorm r_step4C, title("Q-normal Plot: Residuals")
graph save "qnormal_step4C", replace

* //Histogram residuals
hist r_step4C, fcolor(ebg) lcolor(gs15) ytitle("") xtitle("") yscale(off) title("Histogram:
Residuals") normal
graph save "histogram residuals_step4C", replace

* //Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
estat hettest

* //White's test
estat imtest, white

* //Omitted variables test RESET
ovtest

* //VIF
vif

* //Skewness and kurtosis test residuals
sktest r_step4C

* //Durban Wu Hausman test
reg `independent3' `hausman'
predict r_step4C_hausman, res
reg `dependent' `independent3' `mediator' `num_controls' `str_controls' `locational_controls'
`quarter_fe' r_step4C_hausman
test r_step4C_hausman

```

```
log close
```