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Short-term accommodation rental in Amsterdam

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An empirical investigation of statistical correlations between short-term rental, housing prices and quality of life index

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Abstract

This study investigates the emergence and growth of short-term rental (STR) services of accommodation in Amsterdam. More specifically, in its first part it investigates statistical correlations between the emergence and growth of short-term accommodation rentals via collaborative platforms and the development of house prices. In its second part, it assesses statistical correlations between such short-term accommodation rentals and developments in the quality of life, as measured by the "Quality of Life Barometer" (Leefbaarometer).

The research focuses on listings of short-term accommodation intermediated via Airbnb as a proxy for the STR of accommodation via collaborative platforms as this is the largest such platform in Amsterdam. The research uses detailed data and a very fine grain to analyse the topic.

In particular, the relationship between STRs and housing market dynamics is elaborated upon. Results show that the number of STRs is statistically correlated to house price developments at local levels. Evidence for this is found both by means of a hedonic pricing model and a model with a repeat-sales specification. In areas where Airbnb activity already takes place, increasing intensity of this activity is statistically positively correlated with house prices. At the same time, the initial emergence of Airbnb listings is correlated, in certain areas, with a decrease in house prices. These results suggest that the availability of properties for STRs and house prices are subject to a complex process of co-evolution.

With regards to quality of life, the majority of STRs are found in areas with relatively high quality of life. However, when STRs emerge in residential neighbourhoods surrounding the city centre, this emergence can also correlate with a relative decrease of quality of life in these areas, compared to developments in other parts of the city.

This all suggests a complex dynamic between STRs and the city. On the one hand, in certain areas the presence of STRs is statistically correlated with higher house prices and a high quality of life, while in other areas the opposite appears to be the case. It can therefore not be said that STRs are in a specific relationship with the city as a whole, but rather that it relates in different ways. To better understand the relationship between STRs and the city, it is suggested to pay specific attention to the areas where STRs are just establishing, as these areas appear the most dynamic in its interaction with the service.

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1. Introduction

Amsterdam has been very successful in attracting visitors to the capital of the Netherlands. As in other places, a driver for stimulating tourism growth are (expected) positive impacts, as a source of income and employment, in different sectors of the economy. With the continuous increase in the number of tourists, the city of Amsterdam is regarded as an example of a city where tourism increasingly affects the quality of life of residents (Hodes, 2015; McKercher et al., 2015). Debates regarding the negative impacts of tourism on cities, and other types of destinations, have been a part of the tourism canon for over 40 years (Koens et al., 2018; Peeters et al., 2018). However, it has become increasingly clear in recent years that cities not just benefit from tourism, but also may suffer negative effects with regards to the quality of life of city dwellers (Koens et al., 2019). Both in the academic and public debates this development has not gone unnoticed, and *overtourism* is now a well-known concept.

The strong increase of online short-term rental (STR) services has been argued to be one of the main causes of this increase in the (experience of) negative impacts (Nieuwland & van Melik, 2018). A particular issue here, is the impact of STR on house prices, whereby the fear is that STR leads to an increase of house prices and a decrease of the available stock of affordable (private) rental housing. Furthermore, STR activity introduces tourism activity within residential neighbourhoods, raising the potential for functional clashes between urban activities. This can, for example be the introduction of facilities aimed at tourists (e.g. modern cafés) at the expense of local facilities (e.g. grocery store), or annoyances due to noise or behaviour of visitors, which differs from the local norm. Therefore, it may be that STR has an effect on the (perceived) quality of life in a neighbourhood as well as on house prices.

At the request of the European Commission, Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs, *Breda University of Applied Sciences, Erasmus University Rotterdam, HZ University of Applied Sciences and the Centre of Expertise Leisure Tourism and Hospitality* have performed a study on the emergence and development of STR in Amsterdam. More specifically, the study has sought to assess the link between the rise of STR listings in Amsterdam and affordability of housing expressed as house prices. The study also has looked at changes in the quality of life and provides insight with regards to different types of visitors to Amsterdam over the comparable time period. These objectives are researched in the context of tourism development in the Amsterdam area. The research focuses on properties offered for STR via the platform Airbnb, as a proxy for the STR sector, because a very large number of properties are intermediated for STR via this platform in Amsterdam. This leads to the aim of the paper: "*to assess the correlation, for the city of Amsterdam, between the rise of Airbnb listings, the affordability of housing expressed by house prices and the development of quality* *of life."* In order to assess these correlations data of NVM real estate brokers, publicly available web-scraped Airbnb data and data from the Dutch "Quality of Life Barometer" (Leefbaarometer) are combined.

It is particularly difficult to isolate the effects of STR from other elements that impact on house prices and/or quality of life (Mermet, 2017). First, STR emergence and house price increases may co-evolve in more attractive urban areas. Second, it may be that higher income neighbourhood houses simply have more space to host visitors, or houses in these areas may be more desirable objects of investment. Third, reverse causality may be an issue as reduced home affordability may incentivize homeowners to rent out their homes to off-set part of the higher costs of living. Although the focus in this study was on the identification of statistical correlations and its scope does not include any assessment of causality, we do lay the foundation for future assessments of causality by controlling for quality of life at local level and by assessing repeat-sales transactions. The results in this paper can be used to further develop an identification strategy that would allow the claim of causal effects, which this study does not.

The paper is structured as follows. After this introduction, section 2 outlines the theoretical framework, section 3 discusses the area of study and the data. Section 4 details the models estimated to assess the impact of STR on house prices and section 5 discusses the results. Section 6 analyses spatial clusters in the data. Section 7 provides a number of concluding remarks.

2. Online STR services and the urban economy: mixed effects

Tourism is a spatial selective activity, where tourists seek accommodation that is within walking distance of the major attractions (Arbel & Pizam, 1977). Shoval et al. (2011) show that spatial selectivity of tourism locations is mainly driven by hotel location behavior. However, the recent upsurge in online STR services changes this local dynamic, as they start attracting visitors to other parts of the city. As such, localized pressure of tourism, on the functioning of a neighborhood, on the quality of life of inhabitants and on the local housing market, can be intensified with accommodation offered via platforms intermediating properties for STR.

Airbnb is on the most prominent examples of such platforms. The company has accommodated the hosting of over 400 million guests since its launch (Guttentag, 2015) and enjoys considerable market share. Given its size and relevance in the Amsterdam STR market[1], and the fact that properties are often advertised on multiple STR-provider websites, properties intermediated for STR by Airbnb (hereafter: 'Airbnb listings') are used as a proxy for the entire STR offer in Amsterdam.

Gutierrez et al. (2017) show that while hotels and Airbnb listings in Barcelona are both concentrated around the city centre, Airbnb listings cover a wider area and are more evenly distributed. With regard to the location of Airbnb listings, most such listings in five large US cities appear to be clustered around neighborhoods that host a relatively high number of non-family households – households with non-relatives or single person households (Wegmann & Jiao, 2017). In London, Quattrone et al. (2016) distinguish between entire homes/apartments and private rooms and find that the former can mostly be found in areas with many homeowners and high house prices, whereas the latter can be found mostly in areas with greater numbers of non-UK born renters. This demonstrates that the geography of Airbnb listings appears to spread tourists over the city, including to areas that do not traditionally host tourists.

One important discussion point, in the literature but also among the general public and policy makers, is the impact of the growth in number of STR listings on local housing markets. Some empirical studies have already examined the correlations between STR listings and residential markets in the United States and Europe (Barron et al., 2018b; Horn & Merante, 2017; Kim, Leung and Wagman, 2017; Koster

[1] Whilst specific data of different platforms is not available, it is estimated that in 2018 1.98 million bednights were booked via Airbnb, whereas, for example, Homeaway only had 136.000 bookings - https://www.businessinsider.nl/gebruik-van-airbnb-in-amsterdam-voor-het-eerst-in-jaren-gedaald-maar-in-randgemeenten-nam-het-juist-toe/

et al., 2018; Sheppard & Udell, 2016). Although the empirical studies all show correlations between STR listings and property value and rent, the correlations that are established differ between studies and identification of causality is challenging. Sheppard and Udell (2016) argue that a doubling of Airbnb listings is associated with increases in house values of 6 to 11 percent in New York. Using a different type of analysis, they estimate an even larger association and come to an increase in property value of 31 percent. On Anna Maria Island in Florida an increase in the ratio of STRs was found to be related to higher property values, while an ordinance that restricted STRs was related to lower property values (Kim et al., 2017). Using a Bartik-like instrumental strategy, Segú (2018) found that in Barcelona rents were already on the rise prior to the advent of Airbnb, but that Airbnb did have an impact. Notably, an increase of Airbnb density of one percent is related to an increase of four percent in rent. Barron et al. (2018a) find a smaller increase in the USA (2,6 percent). They also find a 1.8 percent increase in rents for a doubling of listings. Horn and Merante (2017) also investigate the effect of Airbnb on rents. They find a one standard deviation increase in Airbnb density correlates to a 0.4 percent increase in local rents. While these effects appear relatively small, the impact strongly depends on the year-over-year average growth rate of STR listings, which can be up to 44% (Barron et al., 2019). In Amsterdam it was found that on average house prices increase by 0,42% in relation to an "increase in Airbnb density by 10,000 reviews posted in a 1,000 meter radius around the property in the period 12 months before the transaction date" (Bijl, 2016, p.2) .

Koster et al. (2018) attribute to Airbnb a modest property value increase of 3 percent in Los Angeles. However, they find a much larger (14 percent) effect in the Central Business District. There are more studies that point out that the effects are not spatially stationary: Garcia-Lopez et al. (2019) demonstrate, in a working paper, that neighbourhoods in Barcelona with a higher penetration of Airbnb experienced an increase of 6 percent in rents and 11 percent in prices. A recent study in the City of South Lake Tahoe in California uses a hedonic regression analysis of home sales and finds that STRs are related to an increase in value of homes near them, but an overall reduction of a city's property values (Wassmer, 2019). Looking at the Greater Dublin Area, Lima (2019, p.88) argues that rising house prices are caused not only by STR, even when "the prominence of Airbnb properties in high-demand areas of the Greater Dublin Area might aggravate the problem".The importance of other factors, besides STR-services, that could influence the rise of house prices come out strongly in several professional reports. The focus in several of these reports is on highlighting the (small) impact Airbnb is expected to have, based on the limited number of houses for which it is possible or makes sense to change from long-term rental to STR. The British Institute for Public Policy Research, while discussing the impact of STR services on London's housing market, used descriptive statistics to argue that in 2015 homesharing did not exert an impact on housing supply or rents[2]. They argue that only a very limited percentage of the housing stock is rented out via STR services and even less is rented out more than 90 days per year. Also, STR services are increasingly used by already functioning commercial operations (e.g. Guesthouses, hostels, B&Bs) as an alternative distribution channel, which suggests these listings are not all suitable for residential habitation. They state that STR services may become more impactful in certain high-pressure boroughs in the future, but for the moment this was not the case. Rather than relating the rise of house prices to homesharing, a lack of supply of new housing and construction was seen as a key issue (Snelling et al., 2016).

In Germany, Empirica (2019) published a report on Airbnb and housing in Berlin, Hamburg, Munich and Dortmund that had similar findings[3], as did a report from SGS Economics and planning in Melbourne and Sydney[4] and a report from CETA in Prague[5]. In Germany, it was also found that homesharing can relieve the pressures on the housing market, as less permanent space is needed for rental to tourists (Empirica ag, 2019), while the report in Melbourne and Sydney found that in the majority of cases, it was not financially more beneficial to host a property on Airbnb compared to renting out to a long-term tenant. This was reported for practically all shared and private rooms, but even for most entire homes/apartments that are rented out (SGS Economics and Planning, 2018)[6].

Some mainstream media articles argue that STR services have a positive relationship with house prices, while there are also articles that specifically argue against a relationship or even an inverted relationship (Baarsma & Dalen, 2016; Hinsliff, 2018). Few of these articles however, provide sufficient methodological information or references for the statements that are made, and some even appear to misinterpret original research (e.g. compare Smith (2018) with Barron et al. (2018a) and Barron et al (2019), which reviews the original report). As such, media reports are deemed unsuitable to judge the merit of STR services.

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[2] For reasons of transparency it is useful to add this research was funded by Airbnb, but that the report states that the contents and opinions in the report are the authors' only

[3] For reasons of transparency it is useful to add this research was commissioned by Airbnb

[4] The report does not engage with non-financial benefits for house owners to rent out via STR services

[5] For reasons of transparency it is useful to add the data for this research was provided by Airbnb

[6] Airbnb further notes that they have calculated the average yearly rental price of housing units for all neighbourhoods in a particular city (based on the website NUMBEO and other external data) and calculated how many days you would need to host on Airbnb to receive such income. In the case of Amsterdam in 2017, it was said that a typical home in Amsterdam would need to be shared for at least 100 nights per year to be more financially attractive than renting it long-term (NB the authors of this report could not verify the methodology of this research).

When it comes to the relationship between STR and quality of life, less has been written. Moreover, much research remains qualitative in nature and focuses on relatively small case-studies. This can be explained by the fact that a concept such as 'quality of life' is fluid and difficult to objectively identify, particularly in comparison to housing prices. Given the context of this study, we relate quality of life particularly to the 'liveability' of a place, to make it possible to conceptualise and clarify the concept. Using this perspective, several common findings can be discerned.

STR services have been argued to help preserve property values and support residents with sufficient additional income to pay or repay mortgages[7] and carry out home renovations, all of which can contribute to a greater quality of life and sense of liveability (Jefferson-Jones, 2014). In addition, STR services can contribute to livelier neighbourhoods and increase the viability of certain type of facilities (e.g. cafés, 'farmer markets') (Koens, Postma & Papp, 2018; Novy, 2018).

STRs are however also reported to negatively impact the quality of life. The rise of STR is argued to be related to a potential loss of amenities aimed at residents (e.g. corner shops) and a general touristification of the neighbourhood. Furthermore, STR decreases the available stock of affordable (private) rental housing. STR can take different forms. It allows for renting out of part of an occupied home (i.e. one or more rooms in a house that in parallel is occupied long-term). It also allows for renting out the entire home if the person renting out the property short-term is not present in the dwelling (either because he/she is absent temporarily or because it is not actually his/her residence). Initially, the philosophy was to increase utilisation if the owner is away from home for instance due to an (extended) holiday. However, houses are also seen as an alternate investment where STR is as a revenue stream. The fact that house owners and investors are able to profit from the STR boom, while people with limited income and private capital are not, can add increasing inequality among residents (Cócola -Gant & Gago, 2019; Roelofsen, 2018; Sans & Quaglieri, 2016).

Next, STR listings are perceived by some people to negatively impact the quality of life due to a loss of facilities, a loss of the sense of community and/or security, particularly if neighbouring dwellings are rented out on a continuous basis (Guttentag, 2015). Common complaints include noise by visitors, issues with traffic and parking as well as insufficient waste management of visitors (Gurran & Phibbs, 2017; Nieuwland & van Melik, 2018). Another commonly reported issue with STR services is that they can be

[7] Results from a survey administered by Airbnb in January 2019, indicate that 39% of hosts say Airbnb provides supplementary income they rely on to make ends meet, while 51% indicate hosting has helped them to afford their homes (NB. the authors of this report could not verify the methodology of these findings)

perceived to contribute to a lack of safety and security. This may be due to a risk of degrading social cohesion as neighbors move out at the expense of unknown people staying for only a few nights. Or, due to a more general anxiety caused by an uncertainty of whether or not people in a neighborhood are residents, and a situation where people no longer know the people next to whom they live (Volgger, Pforr & Reiser, 2018). Particularly in Southern European cities, STRs are blamed by certain groups of residents for causing a loss of local culture and cohesion (Cócola Gant, 2016; Cócola-Gant & Gago 2019). Such sentiments may be less visible in the Amsterdam area.

In sum, STR attracts visitors to residential areas, creating local buzz and entrepreneurial opportunities for homeowners and communities at large, but is also associated with negative external effects. These effects can be argued to be twofold: first, STR listings compete for scarce space, which may drive up prices. Second, STR listings introduce tourism activity within residential neighbourhoods, which can lead to improvements of neighbourhoods but also raising the potential for functional clashes between urban activities (e.g. noise in evenings as people walk home) and issues relating to waste, disturbance and a reduced sense of security (Guttentag, 2015, McKercher et al., 2015). With regards to house prices, a distinction can be observed between academic literature, where conclusions mostly highlight a relation between STR listings and increasing house prices, and practice-oriented reports, where other causes for rising house prices are highlighted more. With regards to social impacts advantages and disadvantages are recognised in both academic and practitioner literature.

This shows that the relationships between STR listings, house prices, geographical spread and liveability are multifaceted and complex. This issue is further exacerbated by “the problem of access to data and the lack of available data to evaluate fully the impact of a sharing economy” (Lima, 2019, p.81; Quattrone et al., 2016; Wegmann & Jiao, 2017). While the impact of STR listings on the way a place changes may be less than the effects of tourism development in general, it can still have a negative effect on the (perceived) quality of life in a neighbourhood, which might again be reflected in house prices. A specific issue here is that it can be difficult to discern the extent to which disturbance is caused by users of STR accommodation rather than day-visitors, commuters or other residents. In addition, the development of STR listings commonly overlaps with a context of more general gentrification (Koens et al., 2018; Van der Zee, 2016). In order to disentangle these relationships a clearer understanding of the bivariate associations and spatial distribution is required.

The relationships between STR activity, house prices and quality of life are summarized in Figure 1.

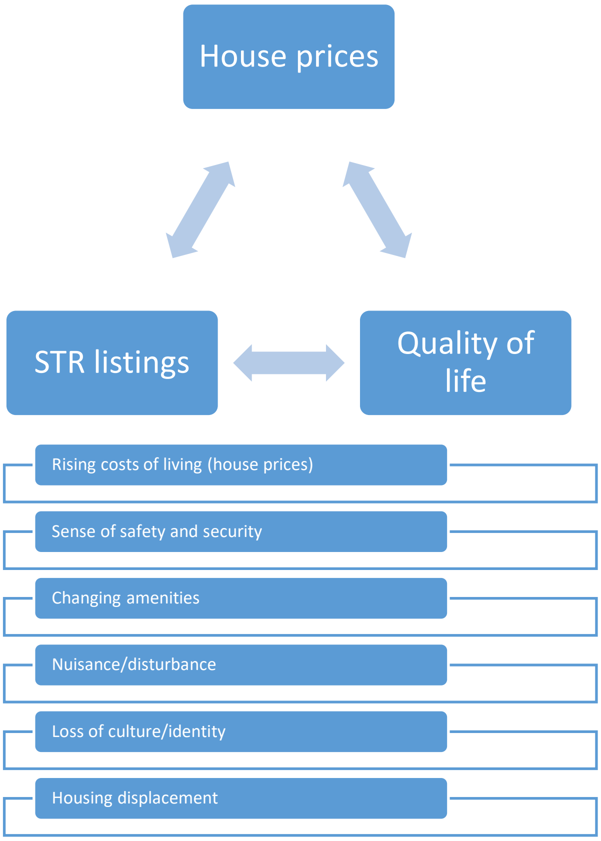

Figure 1: Relationships between STR activity, house prices and quality of life

3. Tourism Developments in Amsterdam

The study has been conducted in the city of Amsterdam. Amsterdam is the national capital of the Netherlands. It has a historic city centre with buildings and canals dating back to the 17th century. Due to its history, wealth of cultural activities and a strong reputation as a libertarian city, Amsterdam has been a popular city-trip destination for a long time and continues to be so. The number of visitors and bednights to Amsterdam, both domestic as well as international has seen a strong increase in recent years (see

Table 1). It is important to note that, based on a recent estimation Amsterdam also attracts a relatively high number of day visitors, with 28 percent of visitors of Amsterdam coming for the day. As daytrippers are less restricted to holiday periods, they are likely to come more also during the low and mid-season (Iamsterdam, 2017).

Table 1: Domestic and international arrivals, bednights and length of stay in Amsterdam (2014-2018)

	Domestic			**International**		
	Arrivals	*Bednights*	*Length of stay*	*Arrivals*	*Bednights*	*Length of stay*
2014	1,412,000	2,340,000	1,7	5,259,000	10,196,000	1,9
2015	1,352,000	2,237,000	1,7	5,474,000	10,661,000	1,9
2016	1,292,000	2,192,000	1,7	5,977,000	11,791,000	1,9
2017	1,477,000	2,463,000	1,7	6,784,000	13,394,000	2
2018	1,654,000	2,826,000	1,7	6,922,000	13,848,000	2

Source: www.tourmis.info

The increase of the number of arrivals is also reflected in the so called 'tourism intensity' in the city, which is calculated by dividing the total number of arrivals in registered hotels and similar establishments by the general population of the city. This has increased on average by 6.8 percent per year in the time period 2014-2017.

Figure 4 shows the spread of arrivals and bednights over the year. The figure shows that Amsterdam receives a relatively steady flow of visitors. Whilst arrivals and bednights are somewhat down in December, January and February, the difference with the peak months is relatively small compared to other cities (e.g. Copenhagen). This might be a potential issue in the context of perceived overtourism, as there is only a limited tourism 'low season'. Such a low season was found to limit perceptions of overtourism, as residents feel they have the city to themselves for at least some of the time (Koens et al., 2018).

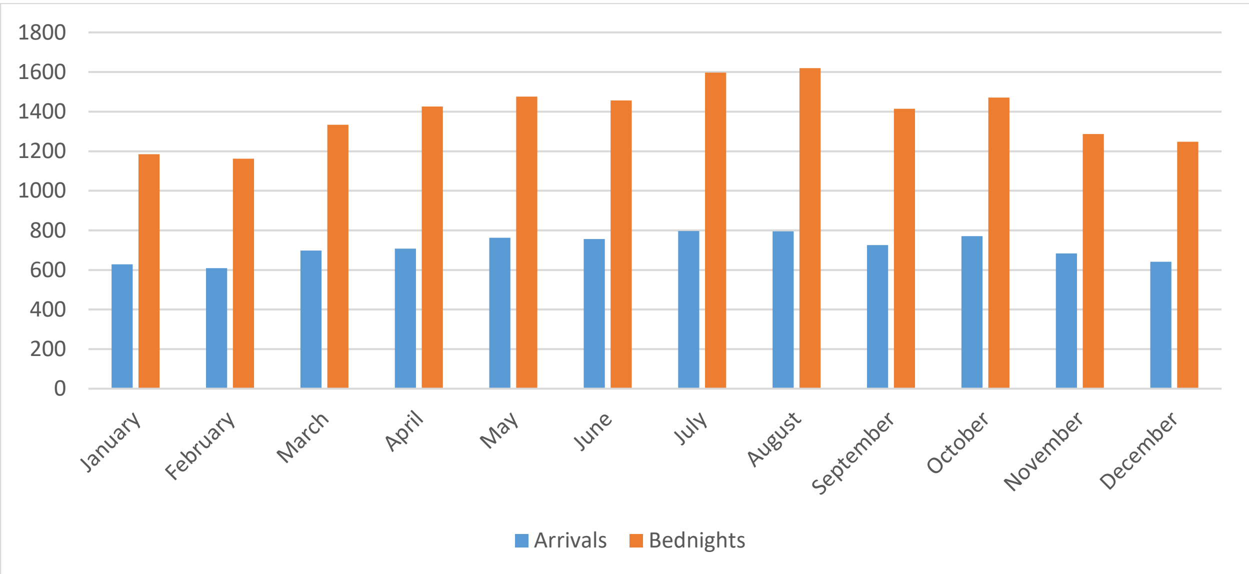

Figure 2: Arrivals and bednights for registered Amsterdam establishments per month in 2018

Currently 7.9 percent of all overnight guests in Amsterdam stay in an Airbnb (Briene et al., 2018). Airbnb guests stay on average 1.5 nights more than hotel guests, which is coherent with the overall trends in major cities (Briene et al., 2018; Haywood et al., 2017). According to records of the municipality of Amsterdam in 2017[8] and 2018[9] one fifth of Airbnb listings in Amsterdam were for accommodations that were rented out as private rooms or shared rooms, while the remainder concerned listings where the entire home or apartment was rented out by individuals, or by licensed and traditional accommodation providers (Gemeente Amsterdam, 2017; Gemeente Amsterdam, 2018). This is confirmed by data provided by Airbnb for 2018 (Table 2).

Table 2: Airbnb listings in 2018

Listings	01-01-2018	01-07-2018	01-01-2019
Active entire home listings	15243	15844	16712
Active private rooms listings	3756	3985	4259
Active shared rooms	64	60	69
Total listings	19063	18989	21040

Listings provided by Airbnb

In trying to manage the impact of STR services, the city has introduced more stringent legislation regulating STR activity in the city. People are only allowed to share their entire home if they are the primary inhabitant of that home. A policy targeted at holiday rental was introduced in January 2017, which Airbnb and Booking.com were the only companies to agree to comply with (van Weeren, 2018). The policy consists of a cap of maximum 60 rental days per year (further limited to 30 days per year per 1 January 2019), a maximum amount of four guests, a payment of tourist tax[10], a mandatory registration for Bed and Breakfasts, as well as increased enforcement of this legislation. While these measures provide some opportunities to restrict strong STR growth, it has proven difficult to enforce regulation, as not all platforms cooperate (Airbnb is one of the companies that has cooperated but disagrees with the limitation of 30 days and does not regulate for this). Airbnb notes that during 2017 and 2018 less than five percent of all entire home listings were rented out for more than 60 days and that this includes hosts with licenses to operate for more than 60 days (for the time period July 2017-July 2018 this number

[8] Gemeente Amsterdam 2017 – Rapportage toeristische verhuur jan-jul, available on: https://hallodepijp.nl/engine/download/blob/gebiedsplatform/69870/2017/50/Rapportage_toeristische_verhuur_jan-jul_2017_DEF.pdf?app=gebiedsplatform&class=9096&id=666&field=69870
[9] Gemeente Amsterdam 2018 – Rapportage toeristische verhuur van woonruimte 2018 – available on: https://assets.amsterdam.nl/publish/pages/909674/pb-114_rapportage_toeristische_verhuur_van_woonruimte_2018.pdf
[10] https://www.amsterdam.nl/bestuur-organisatie/organisatie/ruimte-economie/wonen/regels-verordeningen/reg-vakantieverhuur/ & https://nos.nl/artikel/2145892-Airbnb-beperkt-verhuur-in-amsterdam-tot-60-dagen.html

was higher at 10,6%, but the cap is enforced on a calendar year basis, so several of these listings will be below the cap of 60 days then).

The discussion about the impacts of STR listings, and its legislation, is part of a broader debate on the issue of overtourism. Nonetheless, it is important to realise that the debate on overtourism, also in Amsterdam, is not exclusively related to STR, or even tourism. Overtourism in the city is also associated with increasing crowdedness of the city by tourists, day-visitors, commuters and residents. The relatively high number of daytrippers makes it even more difficult to ascertain causal relations with regards to STR listings, particularly when it comes to 'softer' measurements such as liveability. As such, the study only looks at statistical correlations of observations and does not assess causality.

In looking at the liveability of the city of Amsterdam, the Leefbaarometer (Quality of Life Barometer) of the Dutch Ministry of the Interior and Kingdom Relations is a useful indicator.[11] It was introduced in 2002 and has been updated on a biannual basis since 2012. It provides information on the extent to which the environment fits with the needs and desires of the people who live there. The quality of life of areas is graded, on a scale from very unsatisfactory to excellent. It is based on 100 indicators and is composed of five dimensions*: housing, residents, amenities, safety and physical surroundings.* Each score for a specific dimension is expressed relatively to the national average of that score. Looking at the situation in Amsterdam, the city scores higher than average (compared with the national average) on the categories housing and facilities, while it scores less than average on the other categories. However, the trend in Amsterdam is more positive for all categories, except for the physical surroundings in comparison with the Netherlands. The fact that people are relatively satisfied with the quality of their neighbourhood is confirmed by a report issued by the Amsterdam municipality (Gemeente Amsterdam, 2018). Not only is the average score relatively high (7,54 out of a maximum of 10) but the level of satisfaction has also remained stable or improved in nearly all areas in the time period 2015-2017. The only exceptions were Weteringschans and the Jordaan, which are in the outer parts of the city centre, and two areas in the South East of the city, Venserpolder and Holendrecht/Reigerbos. These relatively high scores and trends indicate that overall people from Amsterdam are relatively content with the liveability of the city.

[11] https://www.leefbaarometer.nl

4. Data sources & Methodology

In this study we combine three detailed data sources to assess the linkages between STR, house prices and quality of life. We employ house prices models (hedonic & repeat sales models) and spatial analysis. In the next three sections the data collection process of the three data sources is elaborated and the data is described.

4.1 Data for STR listings: Tom Slee and Inside Airbnb

Given that a sizeable proportion of STR in Amsterdam is intermediated via the platform Airbnb, we use Airbnb listings as a proxy for STR listings in Amsterdam. Data on Airbnb listings is obtained from two websites, www.tomslee.net and www.insideAirbnb.com. The data on listings, on these websites, is a result of web scraping at irregular intervals during the period of October 2014 until May 2019. Combined, these datasets represent listings scraped at 57 different points in time. There are marginal differences in the scraped data of the two sources, however the geolocation, price, room identifier, host identifier, minimum duration of stay, number of reviews and room type are available in both datasets. The dataset of Inside Airbnb also includes the date of the last review and the average reviews per month, whilst the dataset of Tom Slee does not include these variables. Merging these datasets allows for the analysis of a longer time frame. Data is available starting the second quarter of 2014, up until the second quarter of 2019. Both sources did not scrape the Airbnb website during the fourth quarter of 2014 and the first quarter of 2018. Inside Airbnb started the process of scraping at a later point in time than Tom Slee. Incidentally, Inside Airbnb and Tom Slee both scraped the Airbnb website on the 4th of August 2016, these duplicates are removed from the merged dataset, but are used to assess the validity of the scraping process[12].

The resulting dataset contains both active listings and stale vacancies. Stale vacancies are listings which are present on the Airbnb website, but not actually available for stay. Fradkin (2015) has found that between 21 percent and 32 percent of the inquiries of guests are rejected as a result of stale vacancies. Zervas et al. (2017) has demonstrated three different methods for measuring Airbnb penetration in a city. It was not possible to exactly replicate one of the three methods, since we do not have the date of the last review for all entries. Instead, Zervas et al. (2017) inspired our method. First of all, all listings without a review are excluded from the dataset. This criterion eliminates 13.9 percent of all listings. Furthermore, we expect that active listings obtain more reviews over time. We therefore compose a

[12] Our analysis of these scrapes shows a matching rate of 92 percent, which we deem acceptable. However, it should be noted that web scraping thus can lead to very different results based on the individual choices made by the programmer. Our assessment is included in Appendix A.

variable measuring the change in reviews (delta_reviews) between scrape dates. The descriptive statistics shows that 0.66 percent of all listings show a decrease in reviews, and 68.14 percent of all listings do not show a change in the number of reviews. The remainder (31.2 percent) of listings shows positive change in reviews – and can be assumed to be active[13]. Since data is scraped on an irregular basis, with varying time periods between scrapes, the change in reviews is transformed to a daily measure (delta reviews_per_day) for measuring the level of activity. For inclusion in our dataset, listings with a change in reviews greater than zero are selected[14].

We assume that Airbnb listings have the strongest association with transaction prices closest in time to the transaction. Therefore, we code the listings by year and quarter to match listings and transaction in time. For each quarter, we code Airbnb listings as well as changes in reviews and we use these data to distinguish the local density of active listings. Due to the nature of the construction of our dataset, each first quarter an Airbnb location is listed, it will have a missing value for the computed change in reviews. We assume that new Airbnb listings are by definition active, as the host lists the property with the intention of attracting guests[15]. The final dataset for Airbnb listings in Amsterdam contains 308.716 observations of 50.520 unique Airbnb listings.

When mapping the Airbnb listings, we can clearly see that the number of listings has increased (see Figure 3). The maps in Figure 4 visualise the co-occurrence of Airbnb listings over space within a range of 150 meters. Darker shaded areas represent places where more Airbnb listings are present within 150 meters. We employ this particular distance because our results further on are also based on 150-meter rings (see section 4.2). The left-hand map in figure 4 shows just a few hotspots, while the right-hand map shows many locations in the centre of Amsterdam where a large number of Airbnb's are present. Jointly, Figures 3 and 4 show that over a period of five years Airbnb listings have increased very substantially and that these are mainly concentrated in the centre of the city.

[13] When delta_reviews is studied, some observations have a negative delta_reviews. This is peculiar, since Airbnb states that you cannot delete reviews. Airbnb can remove reviews when they violate their guidelines (Airbnb, n.d.). Since this represents less than 1 % of our dataset, we do not view this as problematic.

[14] The active listings definition of this research report differs from Airbnb's definition for active listings, therefore no direct comparison can be made (see appendix A).

[15] This can be tested at a later stage by comparing our results for both cases (active listings vs. active & new listings).

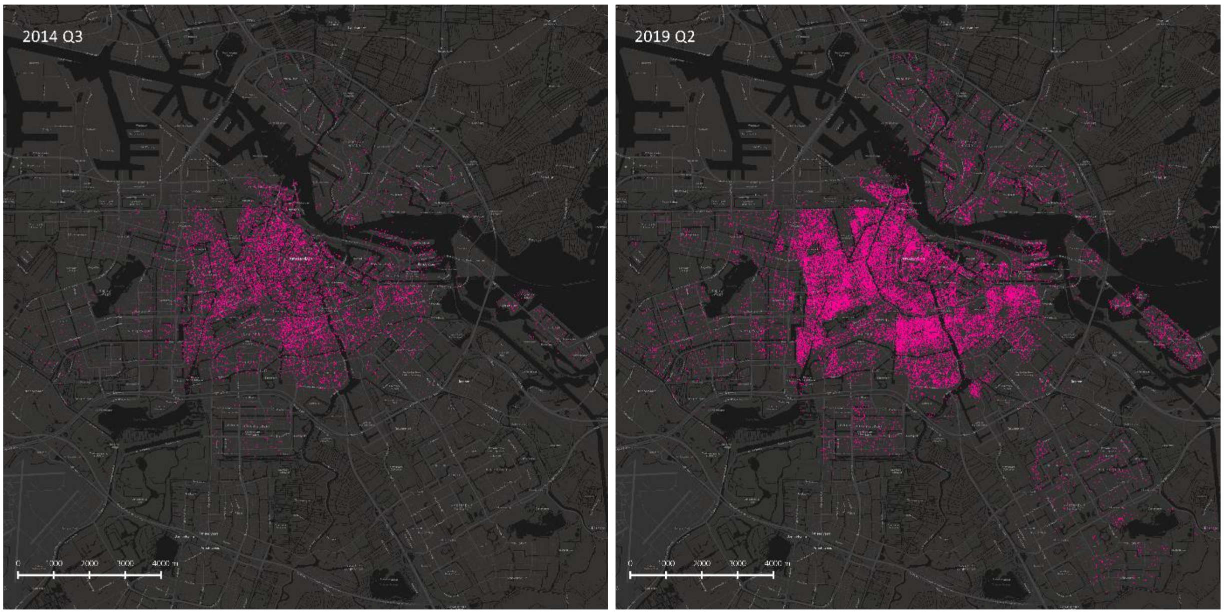

Figure 3: Airbnb listings in Amsterdam by year and quarter (2014 Q3 - left / 2019 Q2 - right)

Figure 3: Spatial concentration of Airbnb listings on the same scale (r=150m, max. 50 listings)

4.2 Data for house transaction prices: NVM data

We use data of the Dutch Association of Realtors (NVM) to measure house transaction prices in the owner-occupied market. We construct a dataset of dwellings that were sold from 2014 to 2019. The dataset contains information on structural characteristics and addresses, these are geocoded to include location characteristics[16]. We start out with 48,155 transactions, distributed over 21 quarters and use 43,495 transactions in our analysis. We find that the number of transactions shows a decreasing trend[17].

Table 3: Distribution of transactions over quarters

Year and Quarter	Frequency	Percent	Cum.
2014 – 02	2,486	5.72	5.72
2014 – 03	2,501	5.75	11.47
2014 – 04	Not matched	Not matched	11.47
2015 – 01	2,363	5.43	16.9
2015 – 02	3,050	7.01	23.91
2015 – 03	2,701	6.21	30.12
2015 – 04	3,026	6.96	37.08
2016 – 01	2,413	5.55	42.63
2016 – 02	2,943	6.77	49.39
2016 – 03	2,461	5.66	55.05
2016 – 04	2,672	6.14	61.19
2017 – 01	2,003	4.61	65.8
2017 – 02	2,357	5.42	71.22
2017 – 03	2,097	4.82	76.04
2017 – 04	2,347	5.4	81.43
2018 – 01	Not matched	Not matched	81.43
2018 – 02	2,014	4.63	86.07
2018 – 03	1,834	4.22	90.28
2018 – 04	2,161	4.97	95.25
2019 – 01	1,648	3.79	99.04
2019 – 02	418	0.96	100
	43,495	100.00	

Table 4: Descriptive statistics of house price transactions

Variable	Mean	Standard deviation	Minimum	Maximum
Price	413,597	347,676	61,250	5,000,000
Price (w)	399,263	268,472	61,250	1,430,000
Size (m^2)	88.38	50.66	15	800
Volume (m^3)	271.76	177.18	37	3,200
Log of price (w)	12.73	0.56	11.02	14.17
(w) prices are winsorized at 1% to reduce the impact of very expensive properties on the analysis				
n = 43,495				

[16] Geocoding is done using the BAG-register, which is provided by the Dutch government under the PDOK service. Geocoding was successful for 99.8% of the transaction data.
[17] The data for 2019, second quarter, are partial data.

The average dwelling in the dataset is transacted for 414,000 euro and has 88 m^2 of usable floor space[18] and a volume of 271 m^3 (Table 4). Second floor or above low-rise dwellings are the most frequent house type and represent more than half of the dataset (55.87%), first floor low-rise dwellings are the second most frequent category (13.52%). Third most frequent are single family homes (8.39%), followed by portico apartments (8.36%). The canal mansions for which Amsterdam is famous only represent 0.58% of all transactions (Table 5).

Table 5: Frequency distribution of dwelling types

Dwelling type	Frequency	Percentage	Cumulative
Simple	269	0.62	0.62
House boat	77	0.18	0.8
Leisure dwelling	1	0	0.8
Single family	3,650	8.39	9.19
Canal mansion	254	0.58	9.77
Mansion	1,024	2.35	12.13
Residential farm	17	0.04	12.17
Single story	40	0.09	12.26
Villa	160	0.37	12.63
Estate	7	0.02	12.64
First floor low-rise	5,879	13.52	26.16
Second floor or above low-rise	24,302	55.87	82.03
Multi-floor apartment	1,278	2.94	84.97
Portico apartment	3,637	8.36	93.33
High-rise apartment	2,113	4.86	98.19
Care unit	1	0	98.19
Double (first & second floor)	786	1.81	100
Total	43,495	100	

Table 6 shows that properties are transacted for each of the construction year cohorts in the dataset, with a large number of properties constructed before the 1930s (43.83%). This is in line with Amsterdam's character as a capital city with a historic city centre. Figure *4* shows the geographic distribution of the transaction data over the city of Amsterdam. This figure shows that the dataset includes properties transacted throughout the city, with the highest density of transactions concentrating in the densest parts of the city (city centre).

Within our dataset we identify 1,950 properties that have been transacted multiple times during our research window.

[18] As defined by the NEN2580 standard for measuring usable floor space

Table 6: Frequency distribution of construction year cohorts

Cohort	Frequency	Percent	Cumulative
Unknown	10	0.02	0.02
1500-1905	7,758	17.84	17.86
1906-1930	11,257	25.88	43.74
1931-1944	4,187	9.63	53.37
1945-1959	2,039	4.69	58.05
1960-1970	4,100	9.43	67.48
1971-1980	1,405	3.23	70.71
1981-1990	3,940	9.06	79.77
1991-2000	3,930	9.04	88.81
> 2001	4,869	11.19	100
Total	43,495	100.00	

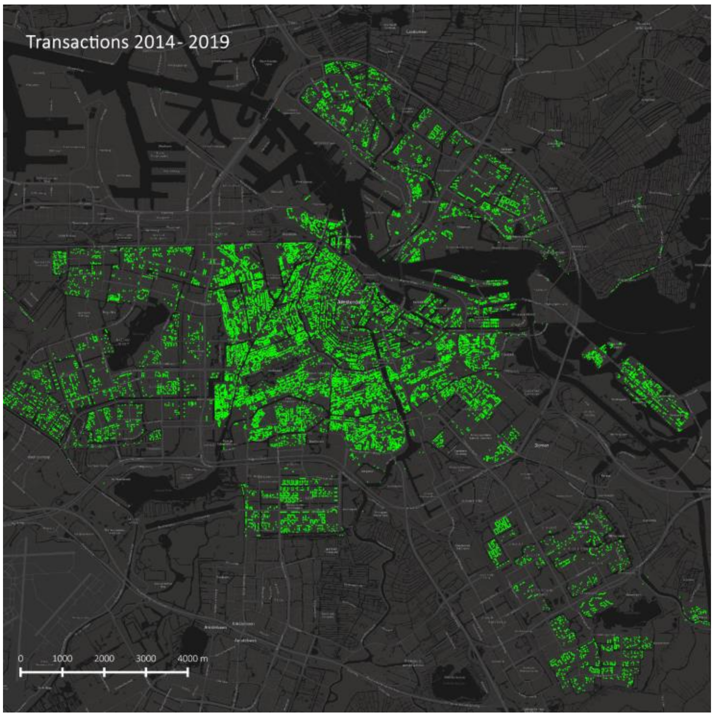

Figure 4: Geographic distribution of transactions 2014-2019

4.3 Data for measuring quality of life: Leefbaarometer

Of the dimensions of the leefbaarometer, the data for Amsterdam is extracted in 100 x 100 meter grids using the *sf package in R* (Pebesma, 2018). To address potential border effects, we buffer the municipal borders of Amsterdam by 0.01 degrees (or 36”), which is slightly larger than our largest distance used in calculations for this study (600 meters). Figure 5, shows the quality of life in Amsterdam in 2018[19]. Overall, quality of life is highest in the inner city, while quality of life in outlying areas is lower.

In Figure 6, we show the change over time. In the period 2014-2016 (left hand side) changes are predominantly positive, with primarily gains in the city centre, while outlying areas show decreases in the quality of life. The right-hand side shows the period 2016-2018, in this period changes in quality of life are mixed, with several pockets of decline in and around the city centre.

As mentioned previously, the Leefbaarometer is composed of five dimensions*: housing, residents, amenities, safety and physical surroundings.* Of these dimensions, safety is considered the most relevant in the context of this research. This will be discussed further in section 6.2.

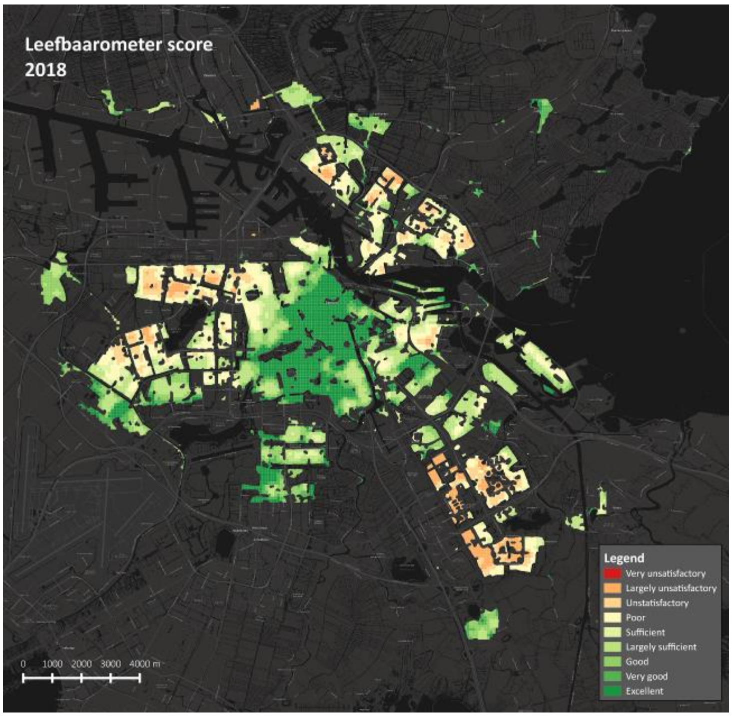

Figure 5: Quality of life (left: 2014 right: 2018)

[19] The quality of life scores are benchmarked against national averages and categorized accordingly. For simplicity we will refer to these simply as 'scores' in the remainder.

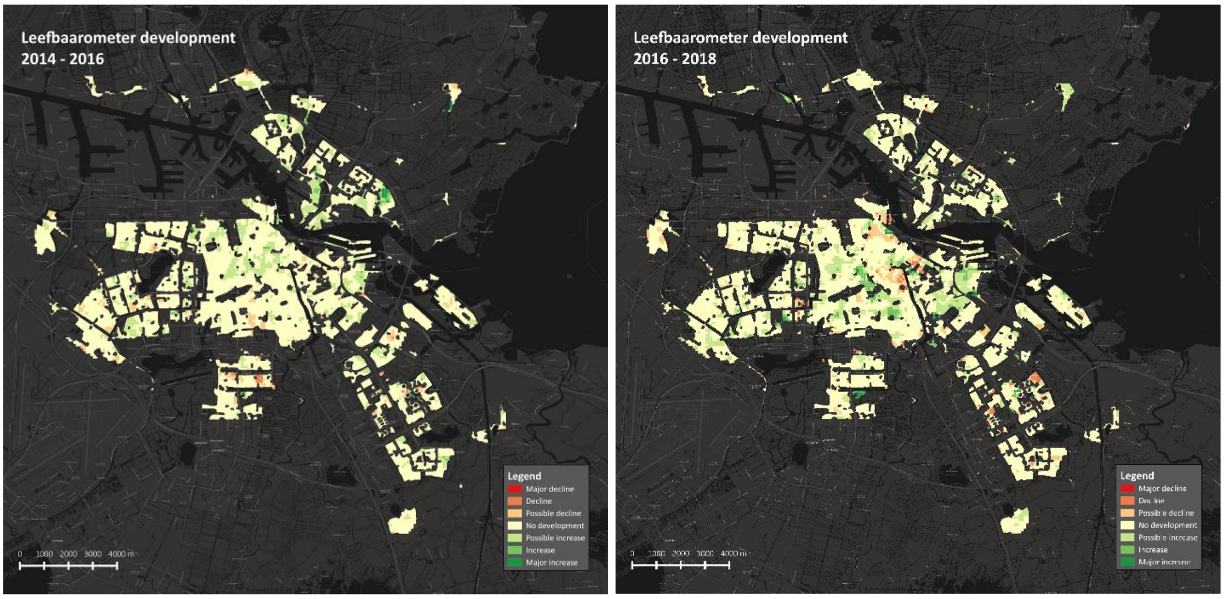

Figure 6: Change in quality of life in Amsterdam (left: 2014-2016, right: 2016-2018)

4.4 Methodology for modelling house prices

In our approach to modelling house prices we follow the dominant approaches in the literature. As housing is a fully product differentiated heterogeneous good (Evans, 2004), the diversity of characteristics is larger than the data available. Each house differs in location, attributes and characteristics. Following the line of work most often attributed to Rosen (1974), we develop a framework where houses are valued for their utility bearing attributes. We follow the structure outlined by Malpezzi (2002), which is commonly used in the literature on hedonic pricing models and elaborate upon this structure by borrowing from the conceptualisation of Li and Brown (1980), who showed a bias in a hedonic house pricing model when micro-neighbourhood factors are not included.

Our model follows the structure:

$V = f(S, N, L, C, T, A)$

Where:

V = is the value as expressed by the (log of) the transaction price, which we winsorize at 1 percent.

S = structural characteristics, in our case the dimensions, construction period, type, maintenance state and amenities of the dwelling.

N = Neighbourhood characteristics, in our case spatial fixed effects at the postal code 4-digit level

L = Location within the market, in our case this is absorbed in our spatial fixed effects, although we control for local quality of life at micro level in some of our specifications and for proximity to the centre in all specifications

C = Contract conditions, in our case detailing lease- or free-hold, tax exemption or foreclosure

T= Time, in our case the year-quarter in which the transaction is observed.

A = Airbnb intensity (elaborated later in this section)

The specifications include two fixed-effects, namely neighbourhood effects and time effects. Our structural characteristics are comparable to previous research on hedonic house price models in the Netherlands (Dekkers, van der Straaten, 2009; De Vor & de Groot, 2011) and inspired by the review of Sirmans (2005) of hedonic studies in the U.S. Additionally we have added the variable *quality of life* in our hedonic price model, which measures the quality of life in inhabited neighbourhoods in municipalities at local level. The variable is added at neighbourhood level and at grid level in two separate specifications, in addition we also check for robustness using the different dimensions of the *Leefbaarometer*[20].

An alternative to the hedonic specification, is a repeat sales specification. We also estimate a repeat sales model to control for unobserved time-invariant heterogeneity between homes. By explicitly taking pairs of sales into account, and calculating the differences, factors such as location, centrality and historic path dependent processes are controlled for. Time variant independent variables in our hedonic model are also differenced and controlled for in this specification. In principle, the repeat sales model is more likely to be unbiased, giving that this model controls for unobserved individual specific effects of the houses. In a sense this model may be considered the 'better' model for this estimate. However, the repeat sales model can only be based on repeat-sales pairs, severely limiting the number of data points available. Therefore, we sacrifice some efficiency in our estimation with this model. In our view, the more elaborate hedonic pricing model and the repeat sales specification are complements, and since both specifications point in the same direction the combination of these to specifications provides confidence in the robustness of our results.

Our main empirical addition is that we match Airbnb listings to houses at micro-level. The number of Airbnb listings is determined based on their geographical location. The geographical location of Airbnb

[20] At the time of writing this paper the 2018 grid data are not easily accessible. We were however able to obtain this data directly from a public server for the purpose of this study and were able to use the most up-to-date data available.

is not exact, since it is anonymized by Airbnb. The given location will be from 0 – 150 meters of the actual address, there is not much known about this distribution. Therefore, we assume that Airbnb listings are distributed randomly over space within 150 meters distance of their actual geolocation. As such, we have chosen for four categories based on intervals of 150 meters[21]. We assume that the measurement bias in Airbnb listings geocoding process is randomly distributed over space. As such, this measurement bias does not introduce bias in our estimates. Figure 7 contains a graphical overview of the calculation of the number of Airbnb listings.

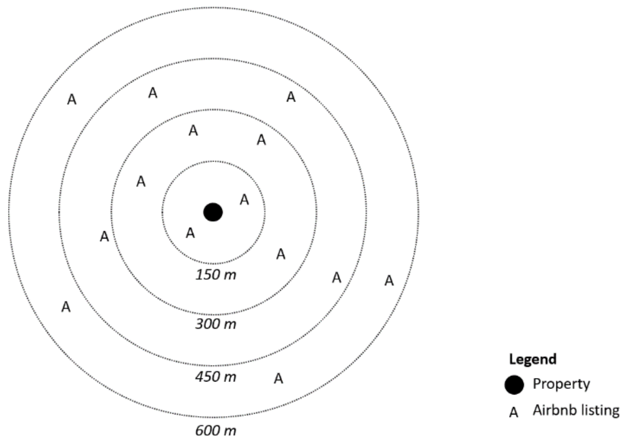

Figure 7: A graphical display of the calculation of the number of Airbnb listings based on geographical boundary

In our model, the number of Airbnb listings will be estimated in four different distance categories. Airbnb listings are matched to transacted properties using a python algorithm[22] where a buffer of radius r in meters surrounding each transacted property is evaluated against the full set of Airbnb listings for the quarter in which the property is transacted. In other words, the algorithm counts the number of active Airbnb listings within r meters around the property. We vary the radius r, to account for varieties in the relationship between Airbnb listings and transacted properties over space. We count the number of Airbnb listings within 150 meters, between 150 and 300 meters, between 300 and 450 meters and between 450 and 600 meters. This results in four variables that represent the number of Airbnb listings within concentric rings surrounding the transacted property. Some transacted properties are surrounded by many Airbnb listings, some as many as 50 or more Airbnb listings. While others are surrounded by no, or only a few Airbnb listings (less than five).

[21] We choose a minimum bandwidth of 150 meters, as this is also the maximum measurement error introduced by in the Airbnb geocoding process as a result of Airbnb's efforts to anonymize listings.
[22] This python script is a variation of the script used in Van Haaren et al. (2017)

We separately code an indicator variable to represent houses without any Airbnb listings in close proximity (within 600 meters). There are 483 transactions in our dataset that have no Airbnb listings in close proximity. Figure 8 shows an example for a specific quarter (Q3 2014 and r=150m) of the result of this matching process. Each dot represents a transacted property. The shading indicated the number of Airbnb listings counted by our algorithm within 150 meters. Darker blue means more counted Airbnb listings. For clarity, we highlighted 'hotspots' of Airbnb activity in red. In these cases more than 40 Airbnb listings are counted within 150 meters of the transacted property. The figure shows that the matching process results in considerable variation in our dataset, some transacted properties are surrounded by many Airbnb listings while some are surrounded by none at all. This creates the opportunity to match variation in counted Airbnb listings to transaction prices.

In addition, we filter for active listings using the change in reviews. The results of this matching process (right hand side of Figure 8) are highly similar to the results for all listings (left hand side). A comparison of the two panels shows that the spatial pattern to all listings and active Airbnb listings is highly similar. Hotspots are in the same places and the intensity of Airbnb listings increases with proximity to the city centre. In the remainder we base our estimates on the set of active Airbnb listings as this represents, in our view, the most interesting data, as actual Airbnb listings usage should influence house prices, not listing.

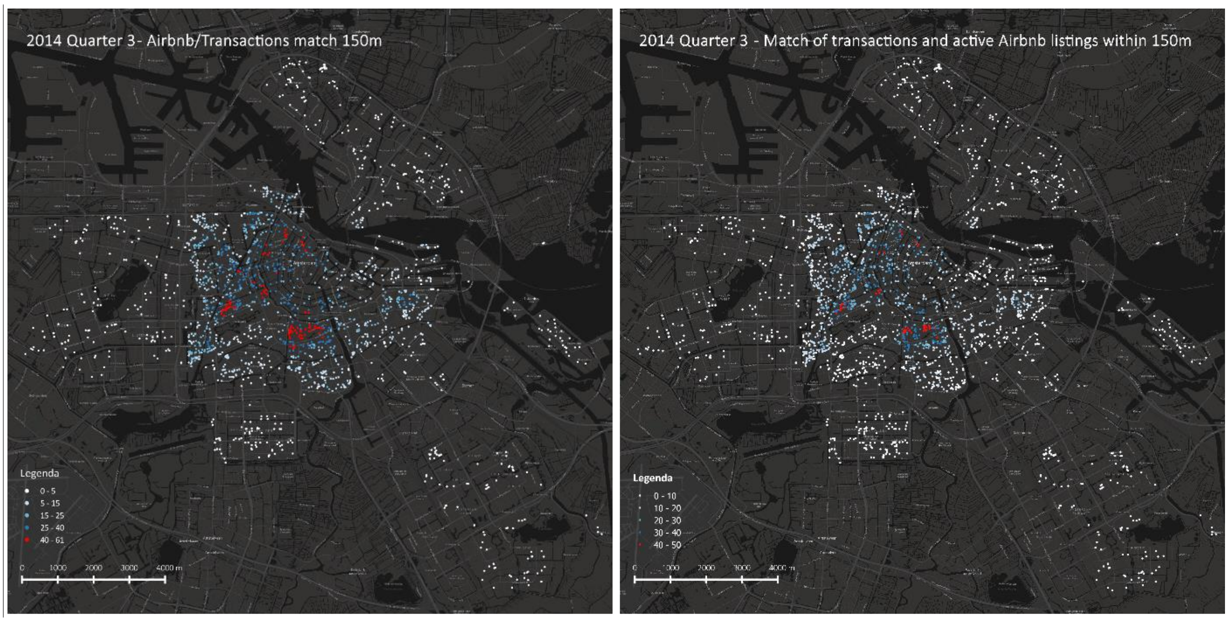

Figure 8: Transaction matching at 150m in 2014 Quarter 3, Left: All Airbnb listings, Right: Active listings.

5. Airbnb emergence and intensity and house prices development

We estimate a base model, which resembles traditional hedonic models as commonly estimated in the literature[23]. The full results are included in appendix B. The coefficients in our base model have the expected sign and the magnitude of the coefficients conforms to reasonable assumption for the Amsterdam housing market. Summarizing these results: all coefficients related to size are positive. Large homes, on larger plots, with more rooms and higher ceilings (volumes), are more expensive c.p. The price-elasticity of size is 0.77, which suggests decreasing marginal willingness to pay for larger homes. The most frequent dwelling types also show coefficients which conform to our expectations a priori. Single family homes are at a premium in Amsterdam, compared to apartment types (such as high-rises) c.p. Our results on construction periods nicely conform to earlier work, suggesting that newer homes are at a premium, unless homes have historic significance (roughly the pre-war period), which is indicative of vintage effects. Furthermore, homes located on land which is under leasehold are cheaper compared to freehold, while the advantage of tax exemption (~2 percent) are fully capitalized into homes. In addition, foreclosed homes are substantially cheaper (~18 percent). Moreover, partially rented homes also fetch a lower price, as rent legislation is stringent. Maintenance is capitalised into house prices, in particular interior maintenance.

Homes with private parking, a garden (especially facing the sun) and with an elevator fetch premiums. Finally, our year quarter dummies conform nicely with recent development on the Amsterdam housing market, and our spatial effects suggest that locations near the city centre are most expensive as well as those in the corridor between the city centre and the 'Zuidas', which is the prime office location in the Netherlands, and proximity to the city centre is valued positively. Based on the results presented, as well as the strong explanatory power of our model[24], we believe our base model to be reliable and a good starting point for evaluating the conditional correlation between the evolution of Airbnb and house prices.

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[23] Our base specification is extensive in parameters. On purpose we estimate an elaborate model, so as to reduce the probability of obtaining spurious results due to omitted variable bias. A concern with a model with so many parameters is overfitting. To control for overfitting we estimate a more parsimonious model including just the log of size, whether the dwelling is an apartment or not, distance to the centre and our Airbnb variables. This model shows an R^2 of 0.79 and effects of the same sign and significance, but with inflated coefficients (due to omitted variable bias). In our view, this shows that overfitting is not a concern in our more elaborate specification.

[24] Our base model yields an R^2 of 0.94. We have analyzed the robustness of our base model using random subsamples to predict out of (sub)sample. These results support a robust base model. These results are summarized in appendix D.

Table 7: Results on Airbnb availability (full results in appendix B)

Log of transaction price	Base	Base + Airbnb
Log of dwelling size (m2)	0.770***	0.772***
	(0.004)	(0.004)
No Airbnb's within 600 meters		0.042***
		(0.007)
Log of nr. of Airbnb listings between 0 – 150 meters		0.003**
		(0.001)
Log of nr. of Airbnb listings between 150 – 300 meters		0.007***
		(0.001)
Log of nr. of Airbnb listings between 300 – 450 meters		0.007***
		(0.001)
Log of nr. of Airbnb listings between 450 – 600 meters		0.007***
		(0.001)
Constant	9.054***	8.944***
	(0.064)	(0.064)
Observations	43,140	43,140
R-squared	0.938	0.939

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

Table 7 shows that the statistical correlation between Airbnb listings and house prices is non-trivial but complex. It shows that properties with no Airbnb listings within close proximity (600 meters), fetch a premium of 4.2 percent. However, of those properties that have one or more Airbnb listings in close proximity, we find that an increasing number of Airbnb listings is also statistically correlated with higher house prices and this correlation becomes stronger with distance from the dwelling. If the number of Airbnb listings within 150 meters of a house is twice as large, we observe house prices that are 0.3 % higher, c.p. Between 150 and 600 meters a doubling of the number of Airbnb listings is statistically correlated with 0.7% higher house prices, c.p. A potential criticism of table 7 is, that the specification of the Airbnb listings is relatively complex, therefore we separate the 'presence of the Airbnb listings' from the intensity of listings in the two separate specifications.

To assess the robustness of the previous findings, Table 8 provides the results with the homes with no Airbnb's in a proximity of 600 metres filtered from the dataset. Given that these cases are relatively few, it is not surprising that such an analysis shows that the results on intensity (logs) change do not significantly change from those observed in Table 7. These results demonstrate that in those areas where Airbnb listings are present within 600 meters of a dwelling, the intensity of Airbnb listings is positively correlated with dwelling prices.

Table 8: Results on Airbnb availability excluding no-Airbnb (full results in appendix B)

Log of transaction price	Base	Base + Airbnb
Log of dwelling size (m2)	0.770***	0.772***
	(0.004)	(0.004)
Log of nr. of Airbnb's between 0 – 150 meters		0.003**
		(0.001)
Log of nr. of Airbnb's between 150 – 300 meters		0.007***
		(0.001)
Log of nr. of Airbnb's between 300 – 450 meters		0.007***
		(0.001)
Log of nr. of Airbnb's between 450 – 600 meters		0.007***
		(0.001)
Constant	9.046***	8.942***
	(0.063)	(0.064)
Observations	42,701	42,701
R-squared	0.937	0.938

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

In Table 9, the specific presence or absence of Airbnb listings in a proximity of 600 metres is investigated. From this table we can conclude that those locations where Airbnb is not yet present within 600 meters of a home, are associated with prices that are 3.3 percent higher c.p. Although the size of the “Absence of Airbnb’s” coefficient is smaller, the general direction and significance of the coefficient are similar. The difference in coefficient size is explained by the omission of the number of Airbnb’s in this model (intensity of listings).

Table 9: Results on Airbnb availability

Log of transaction price	Base	Base + Airbnb
Log of dwelling size (m2)	0.770***	0.772***
	(0.004)	(0.004)
Absence of Airbnb’s (0 = present, 1 = absent)		0.033***
		(0.007)
Constant	9.046***	9.05***
	(0.063)	(0.071)
Observations	43,140	43,140
R-squared	0.937	0.938

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

A potential concern is that Airbnb listings locations proxy for quality of life and that quality of life is not adequately captured by our spatial fixed effects. This concern has merit, as quality of life is not time invariant, nor is it homogeneous within spatial entities. There is anecdotal evidence that within districts, neighbourhoods and areas, one street is popular while another less so. Therefore, we address this concern by assessing quality of life at a low spatial scale.

To control for the potential omission of quality of life, we exploit the fine grain of our 100 x 100 meter grids and match our housing transaction data to the quality of life data, based on the Leefbaarometer. Quality of life and Airbnb listings location behaviour are also not necessarily independent. If such patterns exist, quality of life may be an omitted variable biasing our analysis of the association between Airbnb listings and house prices. In order to assess this concern, we re-estimated our model including explicit quality of life data both as a composite score as well as by including the separate dimensions of quality of life in our specification (full results in appendix B).

Our results, which include a specification including the quality of life composite score, show that higher house prices are observed when quality of life is higher. Compared to areas where quality of life is not measured (assumed to be average), areas with a ‘good’ quality of life score show prices which are 3.5 %

higher, c.p. While areas with 'very good' or 'excellent' quality of life show prices which are 4.1 and 8.8% higher respectively, c.p. Areas with 'sufficient' or lower quality of life, show lower house prices ranging from -2.5 to -6.2 %, this decline is close to monotonous. In a more detailed specification we include both the overall composite score as well as the underlying determinant dimensions. Our focus in this case are the underlying dimensions. These are measured relative to the national average (as opposed to the absolute overall score). A higher score on one or more of the dimensions implies the observation of higher house prices. A 0.1 point deviation (we measure in tenths of a point as the deviations in our sample are fairly small) from the national average on the safety dimension suggests 3 % higher observed house prices c.p. The environment, housing and amenities scores show lower correlations of 1.6, 1.3 and 0.8 % respectively, while the demographic dimension (residents) shows a much stronger correlation of 5.0 %, c.p.

The results on the Airbnb listings variables suggest that the concern of omitted variable bias due to omitting quality of life has some merit, as the coefficients change slightly (Table 10). However, the change is marginal, and the results hold, therefore we view the degree of omitted variable bias in our base model to be marginal[25].

Table 10: Results on Airbnb availability compared with a model controlling for quality of life

Log of transaction price	Base + Airbnb+ QoL score	Base + Airbnb + QoL + QoL dimensions
Log of dwelling size (m2)	0.762***	0.757***
	(0.00390)	(0.00386)
No Airbnb's	0.0395***	0.0402***
	(0.00681)	(0.00674)
Log of nr. of Airbnb's between 0 – 150 meters	0.00549***	0.00663***
	(0.00146)	(0.00149)
Log of nr. of Airbnb's between 150 – 300 meters	0.0114***	0.0136***
	(0.00172)	(0.00175)
Log of nr. of Airbnb's between 300 – 450 meters	0.00879***	0.0123***
	(0.00191)	(0.00188)
Log of nr. of Airbnb's between 450 – 600 meters	0.00686***	0.00975***
	(0.00177)	(0.00177)
Quality of life		
Very Unsatisfactory	-0.0606***	0.110***
	(0.00886)	(0.0115)
Largely unsatisfactory	-0.0553***	0.0906***
	(0.00611)	(0.00882)
Unsatisfactory	-0.0616***	0.0520***
	(0.00359)	(0.00608)
Poor	-0.0401***	0.0319***
	(0.00244)	(0.00394)
Sufficient	-0.0245***	0.0114***
	(0.00252)	(0.00294)
Good	0.0344***	0.00124

[25] This is in line with our approach to include spatial fixed effects at a low spatial scale (postal-code 4 digit), which should capture much of the variance at local level due to stationary quality of life factors.

	(0.00254)	(0.00301)
Very good	0.0412***	-0.00903**
	(0.00313)	(0.00413)
Excellent	0.0884***	0.00180
	(0.00299)	(0.00562)
Safety score relative to the national average		0.302***
		(0.0235)
Housing score relative to the national average		0.128***
		(0.0177)
Resident score relative to the national average		0.495***
		(0.0235)
Amenities score relative to the national average		0.0753***
		(0.0198)
Environment score relative to the national average		0.158***
		(0.0135)
Constant	8.885***	8.981***
	(0.0633)	(0.0671)
Observations	43,140	43,140
R-squared	0.941	0.942

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

Additionally, to assess whether our results estimated for the entire city of Amsterdam, are universally applicable to the various districts in Amsterdam, we assess potential spatial heterogeneity of our results (see Table 11). Our assessment shows that the results differ for the different districts of Amsterdam. Interestingly, the association between no Airbnb listings within 600 meters and higher house prices is driven by the results for the district 'Nieuw-West', the results with respect to this variable for other districts are inconclusive or not applicable (as there are no transactions without Airbnb listings within 600 meters). The results on Airbnb listings intensity are heterogeneous between areas.

Table 11: Results on Airbnb availability by district

Log of transaction price	(1) Centrum	(2) Nieuw-West	(3) Noord	(4) Oost	(5) West	(6) Zuid	(7) Zuidoost
Log of dwelling size (m2)	0.779***	0.592***	0.676***	0.792***	0.804***	0.781***	0.578***
	(0.00975)	(0.0121)	(0.0170)	(0.00967)	(0.00580)	(0.00780)	(0.0177)
No Airbnb's		0.0321***	0.0709				0.0245
		(0.0116)	(0.0523)				(0.0150)
Log of nr. of Airbnb's between 0 – 150 meters	-0.00668	-0.0126***	0.00929**	0.0173***	0.0176***	-0.00601*	0.0125**
	(0.00660)	(0.00279)	(0.00432)	(0.00343)	(0.00368)	(0.00319)	(0.00510)
Log of nr. of Airbnb's between 150 – 300 meters	0.0232**	0.00174	-0.0111***	-0.00246	-0.0170***	0.00518	-0.00164
	(0.0102)	(0.00271)	(0.00424)	(0.00447)	(0.00525)	(0.00419)	(0.00450)
Log of nr. of Airbnb's between 300 – 450 meters	0.00618	0.00444	-0.00756	-0.00630	0.0143**	-0.0185***	0.00613
	(0.0116)	(0.00294)	(0.00485)	(0.00523)	(0.00629)	(0.00480)	(0.00436)
Log of nr. of Airbnb's between 450 – 600 meters	0.0746***	-0.00602**	0.00160	0.00986**	-0.00971	-0.0182***	0.00212
	(0.0126)	(0.00287)	(0.00438)	(0.00429)	(0.00614)	(0.00480)	(0.00428)
Constant	8.759***	10.10***	9.830***	9.008***	8.752***	9.067***	9.285***
	(0.124)	(0.120)	(0.287)	(0.222)	(0.294)	(0.453)	(0.156)
Observations	5,501	5,271	3,473	6,797	9,784	10,245	2,058
R-squared	0.925	0.924	0.927	0.924	0.940	0.942	0.928

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

A valid question is whether there is accurate control for all relevant factors affecting house prices, even unobserved time invariant factors. A strategy to control for such omitted variables is to estimate a repeat sales model. This model exploits multiple sales pairs by estimating the determinants of price change. The results in Table 12 are similar in nature to the previously presented cross-sectional results of the hedonic model. The repeat-sales model suggests that homes in neighbourhoods where Airbnb listings emerge, are correlated with relatively lower prices[26]. However, those areas where Airbnb listings are already present and the density of Airbnb listings is increasing, are correlated with stronger price increases. This again points to the duality in the coevolution of Airbnb listings and house prices. However, the repeat sales specification shows stronger evidence of a negative association compared to hedonic specification. We again break down these results into the different districts of Amsterdam. While these results are not conclusive, as the number of pairs is limited, which makes it difficult to draw robust conclusions, the results are also suggestive of different associations between Airbnb listings and house prices in different districts of the city.

Table 12: Repeat sales results (full results in Appendix C)

% change in transaction price (w=0.025)	Repeat Sales
% change dwelling size (m2)	0.991***
	(0.106)
% change in interior maintenance state	0.0886***
	(0.0188)
% change in exterior maintenance state	0.0394
	(0.0367)
Airbnb emerging in neighborhood	-0.127***
	(0.0448)
% change in nr of Airbnb within 150 meters	0.0108***
	(0.00400)
% change in nr of Airbnb within 150-300 mtrs	0.00608
	(0.00383)
% change in nr of Airbnb within 300-450 mtrs	0.00677
	(0.00450)
% change in nr of Airbnb within 450-600 mtrs	0.0112**
	(0.00457)
change in quality of life	0.0166
	(0.0205)
change in safety score relative to average	0.0965
	(0.291)
change in housing score relative to average	0.667*
	(0.376)
change in amenities score relative to average	-0.104
	(0.235)
change in environmental score relative to average	0.111
	(0.185)
change in residents score relative to average	-0.653
	(0.402)
Constant	-0.0149
	(0.0105)

[26] The authors again controlled for changes in Quality of Life. However, this yielded similar results to the hedonic model specification and are therefore not further elaborated.

Observations	1,935
R-squared	0.730

Table 13: Repeat sales results by district

% change in transaction price (w=0.025)	(1) Centrum	(2) Nieuw-West	(3) Noord	(4) Oost	(5) Zuid	(6) Zuid	(7) Zuidoost
% change dwelling size (m2)	0.735*** (0.187)	0.766*** (0.176)	0.911*** (0.302)	0.885*** (0.216)	0.943*** (0.0818)	1.143*** (0.274)	0.0328 (0.237)
Airbnb emerging in neighborhood		-0.111* (0.0574)	0.218* (0.126)				-0.165* (0.0954)
% change in nr of Airbnb within 150 meters	0.00319 (0.0132)	-0.00116 (0.00582)	0.0143 (0.0137)	-0.00149 (0.00721)	0.0144* (0.00854)	0.0166 (0.0121)	-0.00717 (0.0163)
% change in nr of Airbnb within 150-300 mtrs	-0.0460 (0.0455)	-0.00372 (0.00531)	0.00415 (0.00834)	-0.00409 (0.00911)	-0.00989 (0.00692)	0.0179** (0.00897)	0.0178* (0.00977)
% change in nr of Airbnb within 300-450 mtrs	-0.00525 (0.0547)	-0.00291 (0.00648)	0.00284 (0.0121)	-0.00518 (0.00827)	0.0327** (0.0152)	0.0158 (0.0126)	-0.00433 (0.0120)
% change in nr of Airbnb within 450-600 mtrs	-0.00664 (0.0578)	0.00442 (0.00687)	-0.00449 (0.0119)	-0.00521 (0.00798)	-0.0197 (0.0200)	0.00224 (0.00523)	0.0172 (0.0119)
Constant	0.000667 (0.000884)	0.0640 (0.0457)	-0.0956 (0.0754)	-0.00511 (0.00677)	0.00509 (0.00535)	-0.00392* (0.00216)	-0.0313 (0.0901)
Observations	263	302	157	311	347	459	96
R-squared	0.668	0.830	0.805	0.850	0.828	0.766	0.934

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

In sum, this section shows two different statistical correlations between Airbnb listings and house prices. Estimated over the entire city of Amsterdam, the results on the one hand suggest that the emergence of Airbnb listings in a location is statistically correlated with local observations of lower house prices. On the other hand, the results suggest that areas where Airbnb listings are present, show higher prices if the number of Airbnb listings is also higher. When we explore the statistical correlation between Airbnb listings and house prices in the different districts of Amsterdam, we find evidence that this correlation differs by district, reinforcing the insight that the Airbnb listings – house prices association is not spatially stationary. This requires a more detailed look into the patterns to Airbnb listings, house price and quality of life development, which is undertaken in the next section.

6. Visualization spatial clusters in Airbnb listings, house prices, and quality of life

To zoom into the aforementioned spatial patterns, we dive into local spatial correlations of Airbnb listings, house prices development and quality of life. We analyse the patterns of spatial correlation, in order to map the heterogeneity in correlation between our variables of interest. We recognize the limits of spatial econometrics (Gibbons & Overman, 2012), but also view the tools of spatial econometrics as a powerful descriptive tool to clarify the nature of the problem at hand.

6.1 Data used for mapping spatial clusters

As described in section 3, the quality of life data available for this study is measured on a bi-annual basis. In order to compare the different datasets and identify spatial clusters, the data on housing and Airbnb listings needs to be aggregated to the same spatial and temporal scale. Therefore, both datasets are aggregated to 100 x 100 meter grids and the quarterly data is aggregated into bi-annually datasets. Figure 9 provides an overview of the intensity of Airbnb activity in this grid structure. From this figure it becomes clear that Airbnb listings have increased throughout the city of Amsterdam and most prominently in the city centre and the surrounding neighbourhoods.

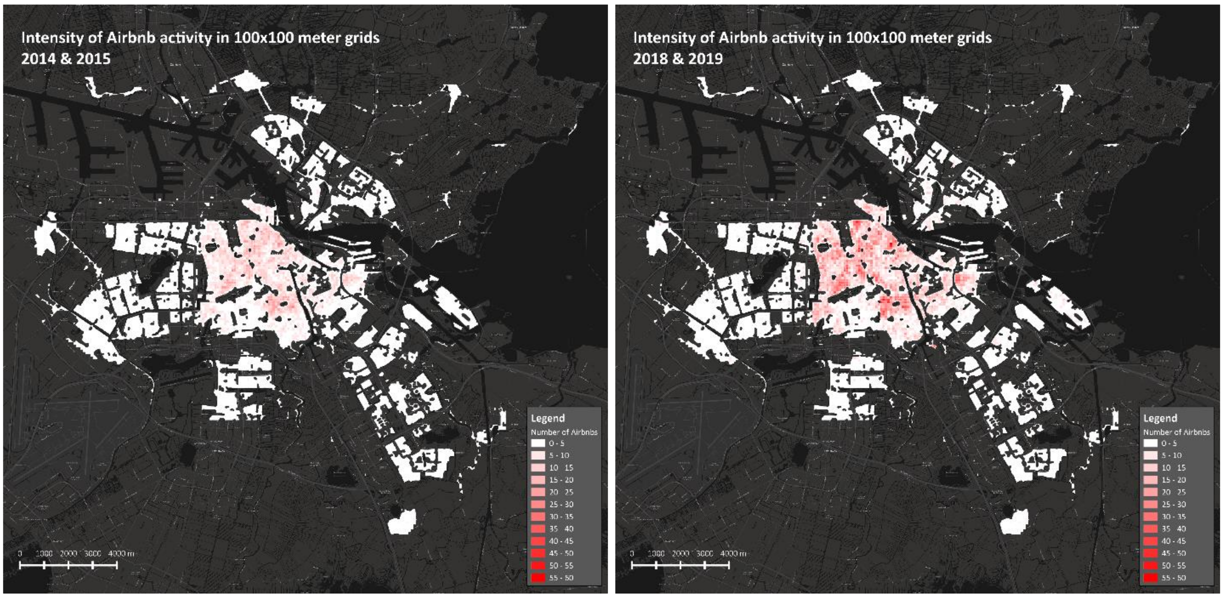

Figure 9: Intensity of Airbnb activity in 100x100 meter grids adjusted to a comparable scale

In addition, Figure 10 provides insights into the average price per square meter at grid level for two sets of two-year periods. This figure shows that the average prices per square meter has risen for nearly all the 100 x 100 meter grids in Amsterdam. It also seems that some specific spots have experienced much larger increases in average house price per square meters than other spots. Visually, the comparison of Figure 9 and Figure 10 suggests a similarity in the pattern of Airbnb listings and price development. The underlying statistical correlation in Airbnb listings development and price development is strongly significant ($p=.000$), but of moderate size ($\rho = 0.20$).

However, as simple correlation requires a one-on-one match of at grid level, this provides a challenge as not every grid has a representative sample of housing transactions in both years and as previously discussed, the geolocation of Airbnb listings is prone to measurement error. Therefore, a more detailed examination requires an approach where spatial matching is somewhat more loosely defined, without giving up the fine grain in our dataset. In our view, spatial econometrics provides a solution in providing tools for spatial association, allowing for a more robust exploration of the association between our variables of interest.

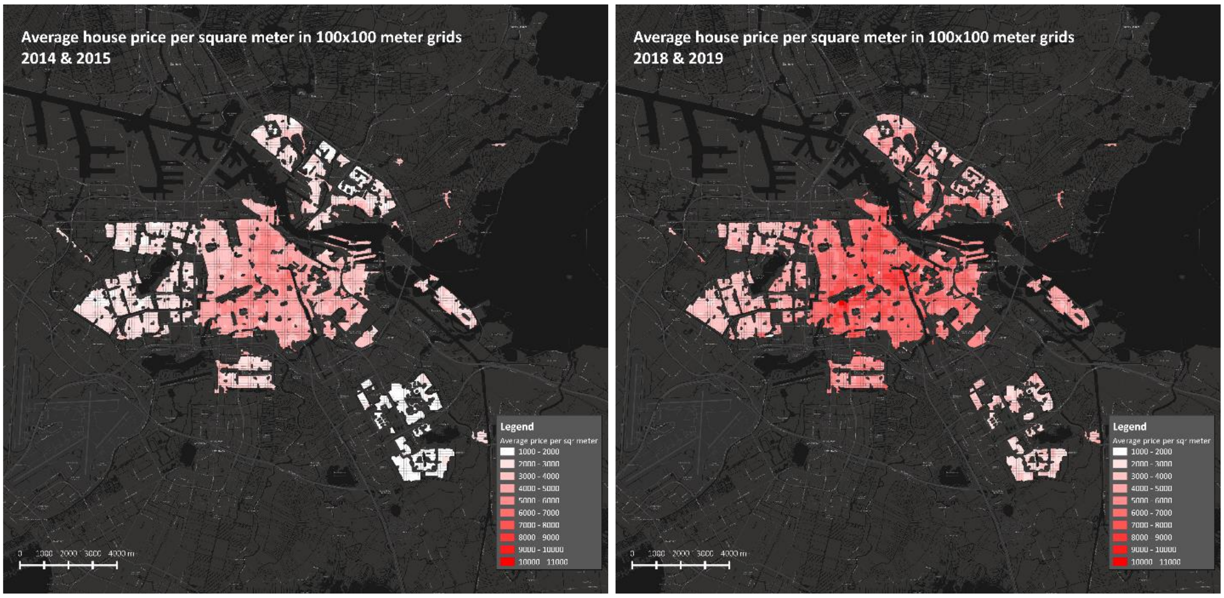

Figure 10: House prices per square meter in 100x100 meter grids adjusted to a comparable scale

We map the data on Airbnb listings, quality of life and house prices by calculating Local Indicators of Spatial Association (LISA) (see Anselin, 1995). By comparing the Airbnb listings LISA in one period (e.g. 2014-2015) to a lagged version of the LISAs for the assumed 'independent' variables house prices and quality of life (e.g. 2016) we can take into account that correlations between variables have to 'ripple through' the local urban economy to become visible. It displays the temporal matching process used for the first wave of comparison. We also estimate a second wave which is two years later for all indicators.

Table 14: Matching between LISAs

Variable one (X)	**Variable two (Y)**
Airbnb listings (2014-2015)	Quality of life (2016)
Airbnb listings (2014-2015)	House prices (2016)

6.2 Quality of life and Airbnb

Figure 11and Figure 12 show the bivariate spatial correlation between our three variables of interest. Figure 11 shows the spatial association between Airbnb listings and house prices.

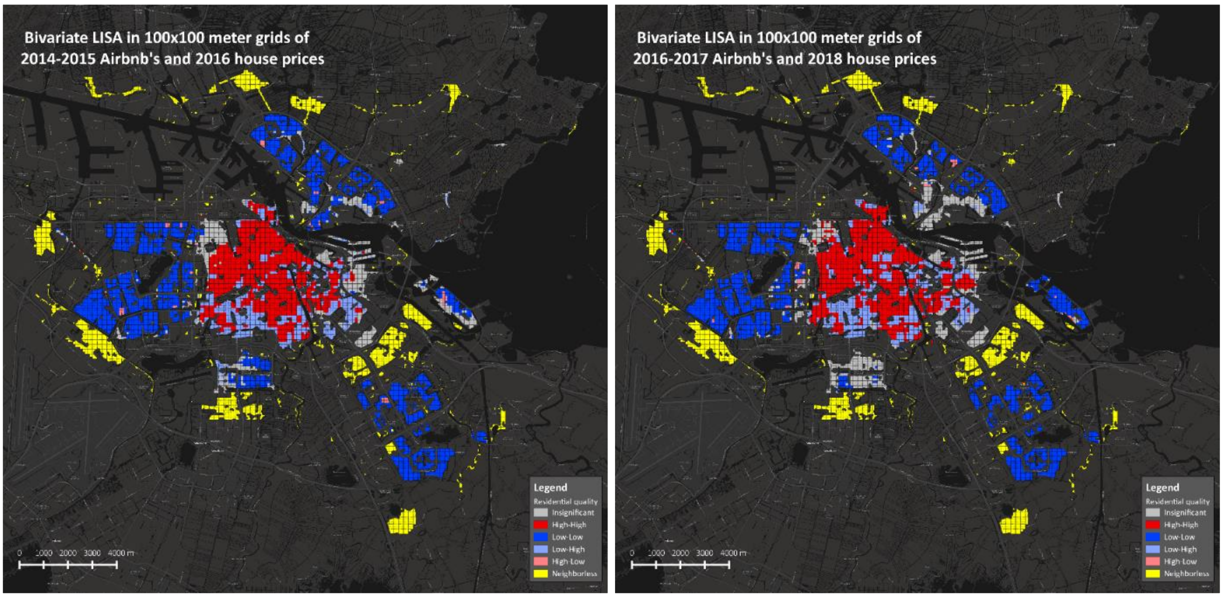

Figure 11: LISA bivariate spatial autocorrelation of Airbnb listings for 2014-2015 and house prices per square meter for 2016 (left) and Airbnb listings for 2016-2017 and house prices per square meter for 2018 (right) based on first & second order queen contiguity

The figure further shows there is a clear centre periphery pattern: In the city centre areas with a high number of Airbnb listings and high housing prices (shared red) are dominant, while many outlying areas show a combination of few Airbnb listings and lower higher housing prices. There are, however, also areas in the centre with high house prices, but limited Airbnb listings (shaded light blue). We conclude from this that price pressure in the city centre is universal, but Airbnb listings sort in specific parts of the centre.

Figure 12 shows the bivariate spatial correlation between Airbnb listings and quality of life. More specifically, it displays the changes within the period of study. Again, the largest cluster is centred over the city centre and it is a cluster of high Airbnb listings and high quality of life (shaded a bright red). Airbnb listings may sort into these areas because of the popularity of the city centre, while simultaneously residents – particular those with a cosmopolitan orientation - also sort into these neighbourhoods to experience the vibrancy of a high density, historic city centre. Conversely, the outlying suburban areas (shaded dark blue) represent areas of low Airbnb listings and low quality of life; Airbnb listings do not sort into these areas – possibly because these areas have a different composition of the housing stock (such as predominantly social housing, which does not allow Airbnb listings or because these areas house urban functions that do not attract tourist).

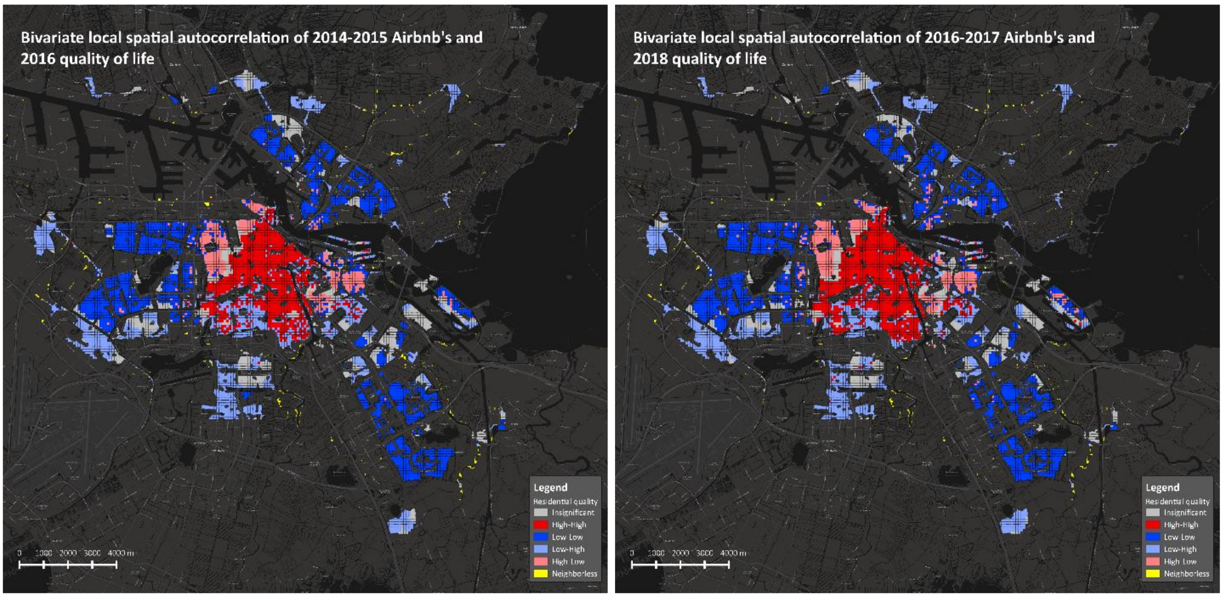

Figure 12: LISA bivariate spatial autocorrelation of Airbnb listings for 2014-2015 and quality of life for 2016 (left) and Airbnb listings for 2016-2017 and quality of life for 2018 (right) based on first & second order queen contiguity

Of particular interest, however, are the lighter shaded areas, where high levels of Airbnb listings are correlated with low levels of quality of life (pink shading) and where low levels of Airbnb listings are correlated with high levels of quality of life (light blue shading). The high-low areas (pink shading) suggest that Airbnb listings are 'flowing into' the neighbourhoods surrounding the city centre. This particularly happens in the Western and Eastern part of city. To the South of the city cente, quality of life is generally of a higher standard. While there appear to be no major changes in the between the two time periods, there does appear to be a small increase of spaces with relatively low quality of life and high Airbnb listings in the Northern part of Amsterdam. This warrants a more localized in-depth analysis.

An important component, and one that is potentially connected to the development of STR, are disruptions and disturbance, which are part of the dimension of safety - in the Leefbaarometer safety is based on six indicators: *nuisance, disturbances, vandalism, crimes, robberies and burglary.* As a final step in our analysis, and as an example of a more detailed analysis, we therefore zoom in on *safety.*

Figure 13 shows the safety score component of the quality of life monitor.

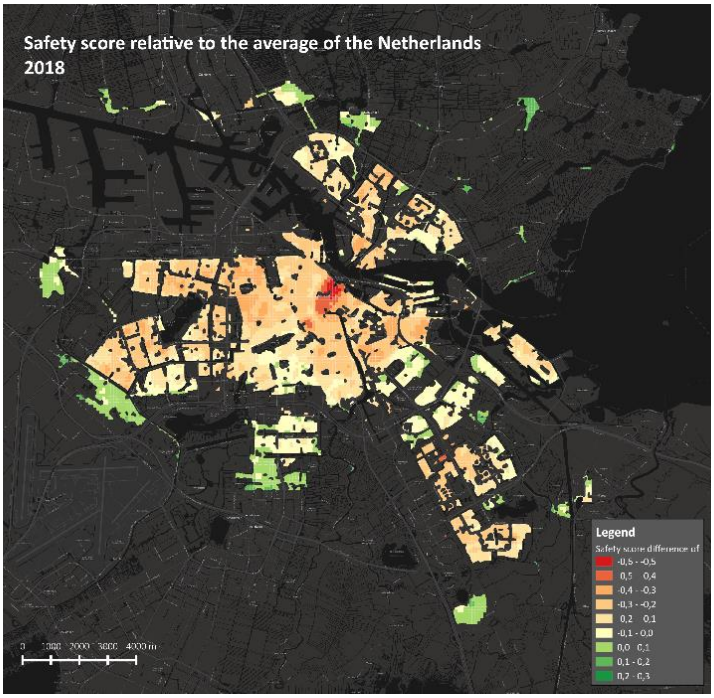

Figure 13: Safety score in relative terms (benchmark: national average)

Relative to the national average, Amsterdam is perceived as less safe. This is to be expected as major cities are in general more prone to experience different forms of nuisance and crime. Unsurprisingly, it is particularly the city centre where the sense of safety is relatively low. At the same time, looking at the areas surrounding the city centre, the places where there is a high presence of Airbnb listings and a low sense of quality of life have a somewhat more negative score in terms of safety. Figure 14 shows a similar picture in highlighting that the general sense of that safety is low in these areas – and that the spatial association is that grids with high numbers of Airbnb listings coincide with spatial proximity of relatively less safe grids. While this again does not provide evidence for casual relations, the statistical correlation between a high number of Airbnb listings and a relatively low quality of life and sense of safety in specific areas, means that these areas require closer scrutiny in follow up research.

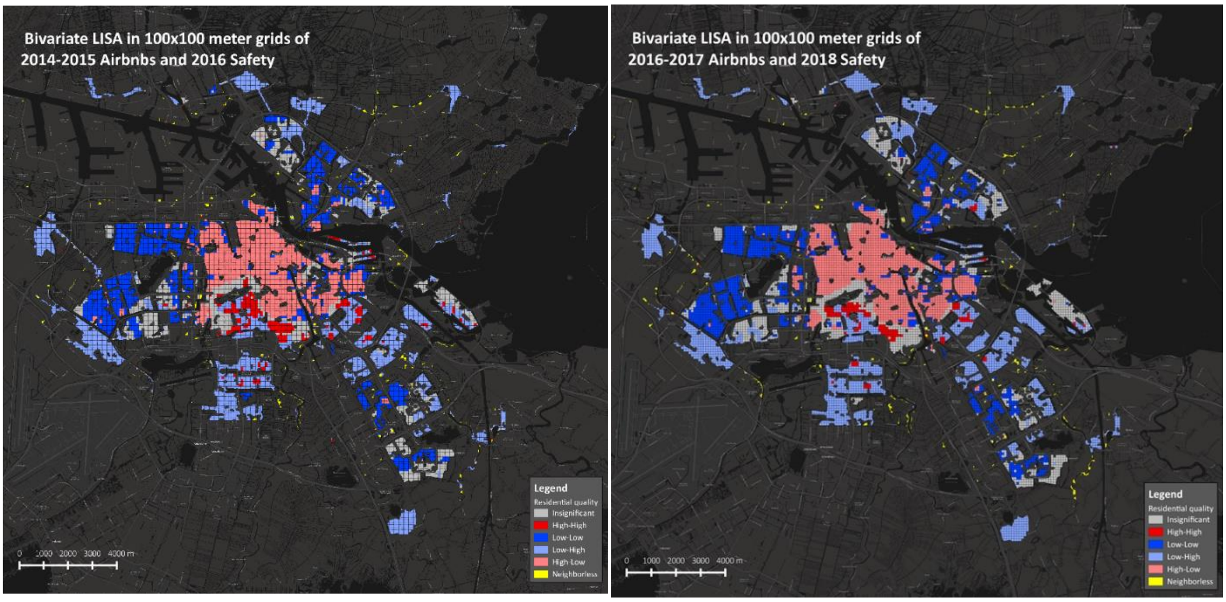

Figure 14: LISA bivariate spatial autocorrelation of Airbnb activity 2014-2015 and the Safety component of Quality of Life for 2016 (left) and Airbnb activity 2016-2017 and the Safety component of Quality of Life for 2018 (right) based on first & second order queen contiguity

Overall, we conclude that there are clear and overlapping patterns in the data on Airbnb listings, house prices development, quality of life and safety. While overall, the correlations are as expected with Airbnb listings mostly visible in the city centre, where house prices and quality of life are high, yet the sense of safety is low, local pockets show reversals. These areas are mostly located just outside the city centre, and historically received relatively few visitors. As such, these areas may prove fertile ground for finding counterfactuals to the rising tide of prices, Airbnb listings and quality of life and therefore these areas require further in-depth study.

7. Discussion

7.1. Conclusions

This study has sought to assess statistical correlations between the pattern of the rise of STR listings in Amsterdam and the pattern of house prices and patterns in the perceived quality of life. This led to its main aim: "*to assess the correlation between the rise of Airbnb listings, the affordability of housing expressed by house prices and the development of quality of life in the city of Amsterdam".* A hedonic pricing model, as well as a model with a repeat-sales specification were used to look at the statistical correlations between house prices and the presence of STR listings and to assess statistical correlations with quality of life. In addition, this model is decomposed into the different districts of Amsterdam, showing spatially heterogeneous results.

The research emphasised the complexity with regards to the potential impact of STR that also has been noted in other work (Garcia-Lopez et al., 2019; Gutierrez et al., 2017; Koster et al., 2018). The results are suggestive in the sense that STR listings, quality of life and house prices are statistically correlated, but also suggest complex correlations that vary spatially. In fact, spatial analysis shows that all three factors are strongly influenced by the forces of urban agglomeration. The high-density city centre, for example, is popular among tourists, has an expensive housing market and scores well on the quality of life measure, which makes disentangling the correlations difficult. This finding confirms earlier work that STR emergence and house price increases correlate in attractive urban areas, like city centres. In the case of Amsterdam during this time period, this correlation can also be observed in seemingly less attractive areas, which may be due to the context of the generally steep rises in house price increases in the period of the research or the fact that Amsterdam has a relatively large share of social housing, which limits the pool of potential STR.

Furthermore, the findings suggest that in certain parts of the city there actually is a negative correlation between Airbnb listings and house prices. In the hedonic pricing specification, homes in areas *without any* Airbnb presence show 5 percent higher observer prices and the repeat-sales specification clearly points to a statistical correlation between areas where Airbnb listings have emerged and *lower* transaction prices. This was mostly evident in areas located around the city centre. Although it cannot be ruled out that these correlations are due to selection effects, it is beyond the scope of the current research to understand the reasons why this is the case and establish a claim of causality.

With regards to quality of life, evidence is found that Airbnb listings and quality of life are mainly positively statistically correlated. However, also in this case we find that in some areas – again mostly located around the city centre - there are opposite correlations.

7.2. Recommendations for further research

- This study has sought to assess statistical correlations between the pattern of the rise of STR listings in Amsterdam and the pattern of house prices and patterns in the perceived quality of life. This led to its main aim: "*to assess, for the city of Amsterdam, the correlation between the rise of Airbnb listings, the affordability of housing expressed by house prices and the development of quality of life".* A hedonic pricing model, as well as a model with a repeat-sales specification were used to look at the statistical correlations between house prices and the presence of Airbnb listings and to assess statistical correlations with quality of life. In addition, this model is decomposed into the different districts of Amsterdam, showing spatially heterogeneous results.

- The positive correlations between house price, quality of life and Airbnb listings are the results of the forces of urban agglomeration.
- The negative correlations between Airbnb activity, house prices and quality of life is due to negative externalities and/or selection effects.

We view this study as the starting point for developing a more sophisticated identification strategy, which can shed light upon these propositions and puts them to the test.

To be able to answer the key question: "*does Airbnb cause changes in house prices?"* we point to the following options: 1) By comparing repeat sales before the introduction of Airbnb listings in 2008 and repeat sales pairs after the introduction of Airbnb listings we can separate out the processes of emergence, growth/decline, as well as potentially restricted Airbnb activity. 2) Our dataset includes all listed Airbnb listings, which include Airbnb listings which are actively listed and rented out, Airbnb listings which are actively listed but not rented out, and stale vacancies. We believe these three groups can be exploited to shed light on the underlying dynamics of the Airbnb listings -house prices relationship. 3) Developing valid instruments that control for Airbnb listings, while being unassociated with the unexplained variance in house prices. 4) Lastly, the different municipalities in the Metropolitan Region of Amsterdam (MRA) have different policies, which were introduced at different moments in time. This variance can be exploited to estimate a regression discontinuity model, in line with Koster et al. (2018). However, such an approach would require more extensive data on Airbnb listings locations, covering the whole MRA, not just the municipality of Amsterdam. If and when such data can be made available, such an approach would be feasible.

While the question whether "*Airbnb causes changes in quality of life?"*, is not the main one in this research, the results have revealed some potentially interesting findings. As such, it would be recommended to further delve into this concept in different ways: 1) theoretically – what kinds of quality of life do Airbnb listings impact on; 2) conceptually– how can quality of life best be measured in relation to Airbnb listings and 3) methodologically – to what extent are the impacts from Airbnb listings specifically caused by Airbnb listings, rather than touristification or the general presence of tourism in general. Earlier work has suggested, that while there is a difference between Airbnb listings and tourism development in general, the two often develop together (Koens et al., 2018), so it would be useful to focus on the specific impacts of each.

The fact that countertrends were found particularly in the areas outside the city centre, leads to the conclusion that such areas are perhaps the most interesting objects of study and also deserve special attention from policy makers. Rather than a city-wide study of the impact of Airbnb listings and other similar STR services, it is recommended to put specific focus on the areas where such services are starting to establish themselves, particularly outside of city centre. It is here that the issue of 'place change' is particularly evident and potentially problematic (McKercher et al, 2015). Two opposing forces may be at work here on the one hand, vibrancy may contribute to an increased quality of life, while on the other hand, the quality of life may be reduced due to nuisance, less social cohesion or a loss in the sense of belonging among residents. As such, it is of great interest to monitor the development of quality of life – as well as its underlying components in these areas. Closer examination of such smaller geographical spaces can at least to an extent, limit the number of variables that need to be taken into account, and make it possible to better understand the specific impact of STR services.

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Appendix A – Matching two separate scrapes

On the 4th of August 2016, Tom Slee (tom slee) and Murray Cox (Inside Airbnb) both scraped "Amsterdam" on www.Airbnb.com. When comparing these two datasets, about 92% of the data matches. This is measured based on room_id and host_id, since these are unique indicators for the room and for the host.

Various factors can influence which information is exactly extracted from the web page. First of all it is highly unlikely both scrape processes started at the exact same time point in a day and that each webpage is scraped at the exact same moment. Additionally the code might contain a time lag to avoid overloading the server with requests. In the code of Tom Slee, which is available on GitHub, this did not happen. It is also possible that Murray Cox and Tom Slee were located in a different time zone. Listings might be missing, because they are fully booked for the near future. It can even be the case that the data is included in one of the two datasets, but not the other. Airbnb hosts can make small adaptations to their webpage which create differences in datasets, like adapting their availability. Another scenario is that page could be temporary down.

When comparing the two datasets, a striking observation can be made. It seems that the prices of identical Airbnb listings are different. The average price based on the removal of the duplicates of Inside Airbnb is calculated, so a listing costs on average around *152.72*. However, the average prices based on the removal of the duplicates of Tom Slee are around *135.39*, which is considerably lower. It could be the case that they are reported in different currencies. Tom Slee states that his price data is collected in $US.

Since our research does not use the variable price of Airbnb, a 92% match of the data seems a good enough match to merge these datasets. As Tom Slee and Inside Airbnb both contribute to have more matches, therefore a more realistic overview of the actual Airbnb listings.

According to Airbnb there are certain issues with scraped data, most notably that the data is scraped on an intermittent basis from the Airbnb website. We acknowledge this, and as described above, also observe differences between the two scraped datasets. To overcome such limitations, also for future research, we would like to suggest that more encompassing listings of STRs are made available publicly by providers of such services, to allow for more detailed and transparent analysis.

Appendix B – Full regression results hedonic pricing model

Log of transaction price	Base	Base + Airbnb	Base + Airbnb + QOL score	Base + Airbnb + QOL dimensions
Log of dwelling size (m2)	0.770***	0.772***	0.762***	0.757***
	(0.00393)	(0.00393)	(0.00390)	(0.00386)
Ceiling height	0.0482***	0.0478***	0.0459***	0.0441***
	(0.00205)	(0.00205)	(0.00203)	(0.00202)
Rooms (w=0.025)	0.0213***	0.0209***	0.0217***	0.0223***
	(0.00125)	(0.00125)	(0.00123)	(0.00122)
2014 Q03	0.0159***	0.0154***	0.0149***	0.0143***
	(0.00422)	(0.00420)	(0.00412)	(0.00408)
2015 Q01	0.0710***	0.0671***	0.0659***	0.0643***
	(0.00426)	(0.00427)	(0.00418)	(0.00415)
2015 Q02	0.120***	0.135***	0.139***	0.144***
	(0.00400)	(0.00413)	(0.00407)	(0.00406)
2015 Q03	0.153***	0.148***	0.146***	0.143***
	(0.00412)	(0.00417)	(0.00409)	(0.00406)
2015 Q04	0.186***	0.174***	0.170***	0.164***
	(0.00396)	(0.00414)	(0.00405)	(0.00403)
2016 Q01	0.230***	0.226***	0.225***	0.222***
	(0.00417)	(0.00423)	(0.00414)	(0.00411)
2016 Q02	0.268***	0.256***	0.252***	0.246***
	(0.00400)	(0.00421)	(0.00412)	(0.00411)
2016 Q03	0.300***	0.280***	0.274***	0.265***
	(0.00411)	(0.00456)	(0.00448)	(0.00451)
2016 Q04	0.336***	0.319***	0.313***	0.306***
	(0.00408)	(0.00446)	(0.00438)	(0.00440)
2017 Q01	0.374***	0.359***	0.353***	0.346***
	(0.00423)	(0.00453)	(0.00447)	(0.00446)
2017 Q02	0.408***	0.388***	0.381***	0.372***
	(0.00409)	(0.00454)	(0.00446)	(0.00449)
2017 Q03	0.433***	0.411***	0.403***	0.393***
	(0.00426)	(0.00481)	(0.00473)	(0.00476)
2017 Q04	0.459***	0.443***	0.437***	0.430***
	(0.00423)	(0.00454)	(0.00446)	(0.00446)
2018 Q02	0.534***	0.514***	0.507***	0.498***
	(0.00440)	(0.00484)	(0.00477)	(0.00480)
2018 Q03	0.558***	0.538***	0.530***	0.523***
	(0.00453)	(0.00491)	(0.00484)	(0.00486)
2018 Q04	0.563***	0.547***	0.540***	0.533***
	(0.00449)	(0.00476)	(0.00470)	(0.00470)
2019 Q01	0.563***	0.555***	0.548***	0.545***
	(0.00471)	(0.00481)	(0.00476)	(0.00472)
2019 Q02	0.576***	0.567***	0.562***	0.556***
	(0.00771)	(0.00773)	(0.00771)	(0.00758)
pc4 = 1012	-0.0538***	-0.0626***	-0.0896***	-0.0637***
	(0.0102)	(0.0101)	(0.0102)	(0.0113)
pc4 = 1013	0.0163*	0.0116	0.0336***	0.000795
	(0.00854)	(0.00851)	(0.00847)	(0.00895)
pc4 = 1014	0.00365	0.0231	0.00113	-0.0595

	(0.0492)	(0.0503)	(0.0436)	(0.0428)
pc4 = 1015	0.114***	0.0932***	0.0716***	0.0452***
	(0.00923)	(0.00937)	(0.00935)	(0.00969)
pc4 = 1016	0.143***	0.120***	0.0807***	0.0474***
	(0.00992)	(0.0101)	(0.0103)	(0.0106)
pc4 = 1017	0.166***	0.148***	0.106***	0.0609***
	(0.00959)	(0.00969)	(0.00993)	(0.0111)
pc4 = 1018	0.0173**	0.0189**	0.0349***	0.00233
	(0.00872)	(0.00863)	(0.00863)	(0.00894)
pc4 = 1019	-0.0246***	-0.0153	0.00243	-0.0553***
	(0.00939)	(0.00937)	(0.00928)	(0.0103)
pc4 = 1021	-0.290***	-0.262***	-0.180***	-0.196***
	(0.0121)	(0.0123)	(0.0125)	(0.0129)
pc4 = 1022	-0.266***	-0.235***	-0.183***	-0.265***
	(0.0182)	(0.0182)	(0.0202)	(0.0207)
pc4 = 1023	-0.0802***	-0.0533***	-0.00719	-0.0957***
	(0.0158)	(0.0162)	(0.0165)	(0.0172)
pc4 = 1024	-0.314***	-0.290***	-0.241***	-0.285***
	(0.0119)	(0.0119)	(0.0121)	(0.0129)
pc4 = 1025	-0.337***	-0.303***	-0.243***	-0.281***
	(0.0115)	(0.0117)	(0.0118)	(0.0117)
pc4 = 1026	0.359***	0.390***	0.349***	0.242***
	(0.0401)	(0.0382)	(0.0409)	(0.0392)
pc4 = 1027	0.115**	0.147***	0.129**	0.00676
	(0.0534)	(0.0547)	(0.0544)	(0.0556)
pc4 = 1028	0.0354	0.0496	0.00939	-0.110*
	(0.0673)	(0.0633)	(0.0601)	(0.0587)
pc4 = 1031	-0.197***	-0.158***	-0.0800***	-0.0976***
	(0.0175)	(0.0181)	(0.0173)	(0.0168)
pc4 = 1032	-0.326***	-0.297***	-0.237***	-0.279***
	(0.0125)	(0.0126)	(0.0125)	(0.0131)
pc4 = 1033	-0.320***	-0.289***	-0.231***	-0.305***
	(0.0116)	(0.0117)	(0.0118)	(0.0122)
pc4 = 1034	-0.363***	-0.329***	-0.265***	-0.293***
	(0.0119)	(0.0122)	(0.0122)	(0.0124)
pc4 = 1035	-0.311***	-0.285***	-0.256***	-0.317***
	(0.0146)	(0.0146)	(0.0146)	(0.0144)
pc4 = 1036	-0.418***	-0.403***	-0.351***	-0.374***
	(0.0196)	(0.0193)	(0.0189)	(0.0188)
pc4 = 1051	-0.0180**	-0.0352***	0.00670	-0.0469***
	(0.00831)	(0.00843)	(0.00858)	(0.00939)
pc4 = 1052	-0.00313	-0.0279***	-0.0134	-0.0355***
	(0.00849)	(0.00874)	(0.00882)	(0.00892)
pc4 = 1053	0.0633***	0.0299***	0.0102	-0.00220
	(0.00861)	(0.00909)	(0.00914)	(0.00975)
pc4 = 1054	0.188***	0.156***	0.124***	0.0817***
	(0.00917)	(0.00963)	(0.00968)	(0.0105)
pc4 = 1055	-0.0828***	-0.104***	-0.0551***	-0.0929***
	(0.00932)	(0.00946)	(0.00955)	(0.00945)
pc4 = 1056	-0.0290***	-0.0558***	-0.0212**	-0.0573***
	(0.00888)	(0.00918)	(0.00925)	(0.00923)
pc4 = 1057	0.00774	-0.0217**	0.0179*	-0.0109
	(0.00944)	(0.00975)	(0.00982)	(0.00976)
pc4 = 1058	0.104***	0.0774***	0.0691***	0.0197*

	(0.0103)	(0.0105)	(0.0105)	(0.0104)
pc4 = 1059	0.165***	0.138***	0.133***	0.0833***
	(0.0116)	(0.0118)	(0.0119)	(0.0118)
pc4 = 1060	-0.102***	-0.117***	-0.128***	-0.176***
	(0.0177)	(0.0177)	(0.0176)	(0.0174)
pc4 = 1061	-0.195***	-0.201***	-0.150***	-0.177***
	(0.0129)	(0.0128)	(0.0127)	(0.0127)
pc4 = 1062	-0.0849***	-0.0886***	-0.0739***	-0.114***
	(0.0146)	(0.0145)	(0.0143)	(0.0142)
pc4 = 1063	-0.275***	-0.262***	-0.222***	-0.237***
	(0.0132)	(0.0132)	(0.0132)	(0.0133)
pc4 = 1064	-0.200***	-0.180***	-0.147***	-0.181***
	(0.0133)	(0.0133)	(0.0134)	(0.0132)
pc4 = 1065	-0.129***	-0.123***	-0.0981***	-0.132***
	(0.0138)	(0.0137)	(0.0138)	(0.0139)
pc4 = 1066	-0.120***	-0.112***	-0.128***	-0.180***
	(0.0147)	(0.0146)	(0.0146)	(0.0145)
pc4 = 1067	-0.227***	-0.220***	-0.194***	-0.222***
	(0.0154)	(0.0154)	(0.0154)	(0.0153)
pc4 = 1068	-0.159***	-0.151***	-0.144***	-0.190***
	(0.0146)	(0.0145)	(0.0144)	(0.0143)
pc4 = 1069	-0.131***	-0.143***	-0.138***	-0.173***
	(0.0163)	(0.0162)	(0.0161)	(0.0159)
pc4 = 1071	0.302***	0.293***	0.243***	0.189***
	(0.0110)	(0.0111)	(0.0113)	(0.0115)
pc4 = 1072	0.126***	0.0933***	0.0597***	0.0542***
	(0.00881)	(0.00927)	(0.00934)	(0.0104)
pc4 = 1073	0.102***	0.0701***	0.0526***	0.0428***
	(0.00900)	(0.00941)	(0.00962)	(0.0104)
pc4 = 1074	0.0875***	0.0600***	0.0378***	0.0259**
	(0.00973)	(0.0100)	(0.0101)	(0.0108)
pc4 = 1075	0.293***	0.274***	0.223***	0.173***
	(0.0117)	(0.0119)	(0.0119)	(0.0121)
pc4 = 1076	0.244***	0.229***	0.206***	0.169***
	(0.0110)	(0.0110)	(0.0111)	(0.0112)
pc4 = 1077	0.355***	0.362***	0.301***	0.241***
	(0.0118)	(0.0118)	(0.0120)	(0.0121)
pc4 = 1078	0.203***	0.185***	0.127***	0.0855***
	(0.0100)	(0.0101)	(0.0102)	(0.0105)
pc4 = 1079	0.151***	0.138***	0.123***	0.0728***
	(0.0104)	(0.0105)	(0.0105)	(0.0106)
pc4 = 1081	0.215***	0.229***	0.179***	0.116***
	(0.0149)	(0.0148)	(0.0148)	(0.0150)
pc4 = 1082	0.146***	0.153***	0.135***	0.0712***
	(0.0131)	(0.0130)	(0.0131)	(0.0133)
pc4 = 1083	0.0847***	0.100***	0.0844***	0.0208
	(0.0126)	(0.0126)	(0.0126)	(0.0129)
pc4 = 1086	-0.0762***	-0.0780***	-0.0795***	-0.116***
	(0.0162)	(0.0162)	(0.0161)	(0.0162)
pc4 = 1087	0.0244	-0.000337	-0.0149	-0.0718***
	(0.0159)	(0.0159)	(0.0159)	(0.0160)
pc4 = 1091	0.0451***	0.0276***	0.0475***	0.0308***
	(0.00878)	(0.00888)	(0.00887)	(0.00885)
pc4 = 1092	0.0419***	0.0283***	0.0620***	0.0500***

	(0.00981)	(0.00985)	(0.00996)	(0.0100)
pc4 = 1093	0.00847	-0.00677	0.0492***	0.0355***
	(0.00938)	(0.00946)	(0.00961)	(0.00957)
pc4 = 1094	-0.0169*	-0.0393***	0.0189**	-0.0189**
	(0.00913)	(0.00931)	(0.00942)	(0.00954)
pc4 = 1095	-0.0512***	-0.0653***	-0.00666	-0.0333***
	(0.0107)	(0.0107)	(0.0108)	(0.0110)
pc4 = 1096	0.0420**	0.0433**	0.0108	-0.0489**
	(0.0207)	(0.0206)	(0.0223)	(0.0213)
pc4 = 1097	0.0494***	0.0644***	0.0660***	0.00806
	(0.0123)	(0.0123)	(0.0122)	(0.0127)
pc4 = 1098	0.102***	0.109***	0.0761***	0.00912
	(0.0114)	(0.0113)	(0.0113)	(0.0119)
pc4 = 1102	-0.305***	-0.302***	-0.274***	-0.278***
	(0.0161)	(0.0160)	(0.0167)	(0.0166)
pc4 = 1103	-0.333***	-0.344***	-0.341***	-0.366***
	(0.0183)	(0.0182)	(0.0179)	(0.0183)
pc4 = 1104	-0.297***	-0.308***	-0.302***	-0.316***
	(0.0206)	(0.0205)	(0.0205)	(0.0206)
pc4 = 1106	-0.131***	-0.153***	-0.173***	-0.220***
	(0.0213)	(0.0211)	(0.0212)	(0.0211)
pc4 = 1107	-0.102***	-0.125***	-0.148***	-0.189***
	(0.0227)	(0.0226)	(0.0225)	(0.0224)
pc4 = 1108	-0.141***	-0.162***	-0.210***	-0.287***
	(0.0213)	(0.0212)	(0.0210)	(0.0209)
pc4 = 1109	0.0961***	0.0741**	0.00163	-0.122***
	(0.0296)	(0.0289)	(0.0290)	(0.0288)
Dwelling type				
Simple	0.0290**	0.0285**	0.0302***	0.0208*
	(0.0116)	(0.0116)	(0.0113)	(0.0112)
House boat	0.0195	0.0149	0.0136	0.0153
	(0.0414)	(0.0410)	(0.0404)	(0.0400)
Leisure dwelling	0.0771	0.0689	0.0826	0.115*
	(0.0614)	(0.0615)	(0.0607)	(0.0641)
Canal mansion	-0.0424**	-0.0425**	-0.0282	-0.0316*
	(0.0192)	(0.0192)	(0.0189)	(0.0189)
Mansion	-0.0293***	-0.0291***	-0.0245***	-0.0216***
	(0.00822)	(0.00821)	(0.00801)	(0.00796)
Residential farm	0.109	0.102	0.0919	0.0896
	(0.0838)	(0.0834)	(0.0819)	(0.0870)
Single story	0.219***	0.219***	0.198***	0.204***
	(0.0381)	(0.0384)	(0.0380)	(0.0376)
Villa	0.0867***	0.0870***	0.0864***	0.0869***
	(0.0232)	(0.0233)	(0.0226)	(0.0225)
Estate	0.216***	0.202***	0.186***	0.154**
	(0.0674)	(0.0710)	(0.0697)	(0.0705)
First-floor low-rise	-0.0200***	-0.0208***	-0.0128***	-0.00674
	(0.00502)	(0.00504)	(0.00496)	(0.00490)
Second floor or above low-rise	-0.0412***	-0.0418***	-0.0354***	-0.0300***
	(0.00515)	(0.00516)	(0.00508)	(0.00503)
Multi-floor apartment	-0.0637***	-0.0646***	-0.0546***	-0.0488***
	(0.00604)	(0.00605)	(0.00593)	(0.00585)
Portico apartment	-0.0434***	-0.0440***	-0.0355***	-0.0296***
	(0.00545)	(0.00546)	(0.00538)	(0.00533)

High-rise apartment	-0.0846***	-0.0855***	-0.0765***	-0.0725***
	(0.00594)	(0.00595)	(0.00585)	(0.00578)
Care unit	0.107***	0.105***	0.0911***	0.0918***
	(0.00743)	(0.00758)	(0.00783)	(0.00786)
Double (first & second floor)	0.00392	0.00303	0.00920	0.0150**
	(0.00764)	(0.00765)	(0.00758)	(0.00751)
Construction period				
Unknown construction year	-0.0256	-0.0228	-0.0332	-0.0527
	(0.0482)	(0.0496)	(0.0463)	(0.0478)
1500-1905	0.0329***	0.0323***	0.0240***	0.0115***
	(0.00394)	(0.00395)	(0.00390)	(0.00386)
1906-1930	0.0185***	0.0173***	0.0176***	0.00597
	(0.00378)	(0.00379)	(0.00374)	(0.00372)
1931-1944	0.0205***	0.0198***	0.0147***	-0.000572
	(0.00421)	(0.00421)	(0.00416)	(0.00416)
1945-1959	-0.0601***	-0.0581***	-0.0551***	-0.0650***
	(0.00521)	(0.00521)	(0.00514)	(0.00522)
1960-1970	-0.135***	-0.133***	-0.123***	-0.136***
	(0.00441)	(0.00440)	(0.00431)	(0.00451)
1971-1980	-0.126***	-0.121***	-0.114***	-0.127***
	(0.00577)	(0.00569)	(0.00554)	(0.00557)
1981-1990	-0.0585***	-0.0583***	-0.0561***	-0.0647***
	(0.00375)	(0.00375)	(0.00368)	(0.00366)
1991-2000	-0.00836**	-0.00840**	-0.0165***	-0.0216***
	(0.00350)	(0.00350)	(0.00345)	(0.00340)
Plot size (w=0.01)	0.000239***	0.000243***	0.000236***	0.000225***
	(2.97e-05)	(3.00e-05)	(2.92e-05)	(2.86e-05)
Lease-hold	-0.0430***	-0.0414***	-0.0371***	-0.0347***
	(0.00190)	(0.00190)	(0.00187)	(0.00188)
Delta Asking price (w=0.01)	9.09e-07***	9.01e-07***	9.25e-07***	9.71e-07***
	(9.46e-08)	(9.45e-08)	(9.32e-08)	(9.24e-08)
Tax exempt	0.0211**	0.0249**	0.0241**	0.0250***
	(0.00998)	(0.00999)	(0.00978)	(0.00967)
Foreclosure	-0.180***	-0.181***	-0.180***	-0.177***
	(0.0266)	(0.0265)	(0.0262)	(0.0260)
Elevator present	0.0241***	0.0257***	0.0246***	0.0196***
	(0.00252)	(0.00252)	(0.00247)	(0.00245)
Interior maintenance state				
Extremely poor	-0.0705***	-0.0699***	-0.0628***	-0.0701***
	(0.0192)	(0.0194)	(0.0190)	(0.0189)
Very poor	-0.0661***	-0.0665***	-0.0637***	-0.0659***
	(0.0240)	(0.0240)	(0.0237)	(0.0235)
Poor	-0.0306***	-0.0312***	-0.0340***	-0.0356***
	(0.00798)	(0.00795)	(0.00777)	(0.00778)
Low	-0.0400***	-0.0414***	-0.0429***	-0.0450***
	(0.0102)	(0.0101)	(0.00995)	(0.00987)
Fair	-0.0341***	-0.0333***	-0.0317***	-0.0320***
	(0.00463)	(0.00461)	(0.00453)	(0.00449)
Good	0.0632***	0.0631***	0.0654***	0.0653***
	(0.00356)	(0.00354)	(0.00347)	(0.00344)
Very good	0.113***	0.112***	0.113***	0.111***
	(0.00515)	(0.00514)	(0.00508)	(0.00502)
Excellent	0.142***	0.143***	0.143***	0.142***
	(0.00451)	(0.00449)	(0.00442)	(0.00437)

Exterior maintenance				
Extremely poor	-0.0768	-0.0789	-0.0975*	-0.0868*
	(0.0574)	(0.0571)	(0.0534)	(0.0520)
Very poor	-0.0175	-0.0133	-0.0101	-0.00663
	(0.0575)	(0.0566)	(0.0570)	(0.0538)
Poor	0.00250	0.00333	0.00455	0.00917
	(0.0198)	(0.0198)	(0.0195)	(0.0196)
Low	-0.00627	-0.00730	-0.00476	0.000288
	(0.0367)	(0.0366)	(0.0363)	(0.0356)
Fair	-0.00604	-0.00631	-0.00640	-0.00386
	(0.00820)	(0.00818)	(0.00804)	(0.00795)
Good	0.0176***	0.0180***	0.0176***	0.0164***
	(0.00510)	(0.00510)	(0.00503)	(0.00493)
Very good	0.0331***	0.0332***	0.0336***	0.0332***
	(0.00660)	(0.00659)	(0.00654)	(0.00641)
Excellent	0.0329***	0.0332***	0.0345***	0.0335***
	(0.00612)	(0.00611)	(0.00603)	(0.00592)
Business space present	0.0108	0.00899	0.00256	0.00838
	(0.0621)	(0.0616)	(0.0595)	(0.0602)
Parking				
Single on-site parking space	0.0281***	0.0294***	0.0275***	0.0263***
	(0.00451)	(0.00450)	(0.00440)	(0.00433)
Carport, no garage	0.0284***	0.0321***	0.0306***	0.0292***
	(0.00385)	(0.00385)	(0.00374)	(0.00374)
Garage, no carport	0.0603***	0.0618***	0.0574***	0.0560***
	(0.00557)	(0.00559)	(0.00545)	(0.00543)
Garage & carport	0.0679***	0.0702***	0.0686***	0.0660***
	(0.00934)	(0.00936)	(0.00895)	(0.00882)
Multi-car garage	0.0957***	0.0962***	0.0896***	0.0863***
	(0.0147)	(0.0148)	(0.0144)	(0.0142)
Garden				
North	0.0551***	0.0552***	0.0547***	0.0542***
	(0.00724)	(0.00723)	(0.00709)	(0.00698)
North-East	0.0434***	0.0437***	0.0476***	0.0454***
	(0.00753)	(0.00754)	(0.00737)	(0.00724)
East	0.0464***	0.0461***	0.0458***	0.0445***
	(0.00519)	(0.00517)	(0.00510)	(0.00501)
South-East	0.0481***	0.0486***	0.0479***	0.0471***
	(0.00514)	(0.00513)	(0.00500)	(0.00494)
South	0.0542***	0.0543***	0.0536***	0.0540***
	(0.00391)	(0.00391)	(0.00385)	(0.00383)
South-West	0.0701***	0.0708***	0.0699***	0.0694***
	(0.00427)	(0.00428)	(0.00421)	(0.00416)
West	0.0493***	0.0495***	0.0501***	0.0494***
	(0.00490)	(0.00490)	(0.00482)	(0.00478)
North-West	0.0493***	0.0503***	0.0520***	0.0527***
	(0.00567)	(0.00565)	(0.00555)	(0.00551)
Designated monument	0.0169***	0.0177***	0.0168***	0.0120***
	(0.00443)	(0.00442)	(0.00435)	(0.00431)
Permanent residence	0.0437	0.0446	0.0515	0.0631
	(0.0608)	(0.0609)	(0.0601)	(0.0636)
Partially rented out	-0.132***	-0.132***	-0.128***	-0.116***
	(0.0369)	(0.0368)	(0.0377)	(0.0384)
Distance to city centre	-7.61e-05***	-6.54e-05***	-5.00e-05***	-4.40e-05***

	(2.05e-06)	(2.24e-06)	(2.26e-06)	(2.30e-06)
No Airbnb's		0.0424***	0.0395***	0.0402***
		(0.00704)	(0.00681)	(0.00674)
Log of nr. of Airbnb’s between 0 – 150 meters		0.00329**	0.00549***	0.00663***
		(0.00148)	(0.00146)	(0.00149)
Log of nr. of Airbnb’s between 150 – 300 meters		0.00685***	0.0114***	0.0136***
		(0.00175)	(0.00172)	(0.00175)
Log of nr. of Airbnb’s between 300 – 450 meters		0.00686***	0.00879***	0.0123***
		(0.00196)	(0.00191)	(0.00188)
Log of nr. of Airbnb’s between 450 – 600 meters		0.00786***	0.00686***	0.00975***
		(0.00181)	(0.00177)	(0.00177)
Quality of life				
Very Unsatisfactory			-0.0606***	0.110***
			(0.00886)	(0.0115)
Largely unsatisfactory			-0.0553***	0.0906***
			(0.00611)	(0.00882)
Unsatisfactory			-0.0616***	0.0520***
			(0.00359)	(0.00608)
Poor			-0.0401***	0.0319***
			(0.00244)	(0.00394)
Sufficient			-0.0245***	0.0114***
			(0.00252)	(0.00294)
Good			0.0344***	0.00124
			(0.00254)	(0.00301)
Very good			0.0412***	-0.00903**
			(0.00313)	(0.00413)
Excellent			0.0884***	0.00180
			(0.00299)	(0.00562)
Safety score relative to the average				0.302***
				(0.0235)
Housing score relative to the average				0.128***
				(0.0177)
Resident score relative to the average				0.495***
				(0.0235)
Amenities score relative to the average				0.0753***
				(0.0198)
Environment score relative to the average				0.158***
				(0.0135)
Constant	9.054***	8.944***	8.885***	8.981***
	(0.0635)	(0.0642)	(0.0633)	(0.0671)
Observations	43,140	43,140	43,140	43,140
R-squared	0.938	0.939	0.941	0.942

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

Appendix C – Airbnb repeat sales model

% change in transaction price (w=0.025)	Repeat Sales
% change dwelling size (m2)	0.991***
	(0.106)
% change in interior maintenance state	0.0886***
	(0.0188)
% change in exterior maintenance state	0.0394
	(0.0367)
Airbnb emerging in neighborhood	-0.127***
	(0.0448)
% change in nr of Airbnb within 150 meters	0.0108***
	(0.00400)
% change in nr of Airbnb within 150-300 mtrs	0.00608
	(0.00383)
% change in nr of Airbnb within 300-450 mtrs	0.00677
	(0.00450)
% change in nr of Airbnb within 450-600 mtrs	0.0112**
	(0.00457)
Quarter/Year last sale in pair	
2014 Q03	0.0663***
	(0.0230)
2015 Q01	0.158***
	(0.0329)
2015 Q02	0.255***
	(0.0329)
2015 Q03	0.263***
	(0.0369)
2015 Q04	0.293***
	(0.0290)
2016 Q01	0.385***
	(0.0325)
2016 Q02	0.407***
	(0.0257)
2016 Q03	0.396***
	(0.0249)
2016 Q04	0.487***
	(0.0260)
2017 Q01	0.574***
	(0.0285)
2017 Q02	0.598***
	(0.0274)
2017 Q03	0.608***
	(0.0302)
2017 Q04	0.672***
	(0.0255)
2018 Q02	0.764***
	(0.0283)
2018 Q03	0.815***
	(0.0276)
2018 Q04	0.826***
	(0.0258)
2019 Q01	0.855***
	(0.0283)
2019 Q02	0.931***
	(0.0416)
Quarter/Year first sale in pair	

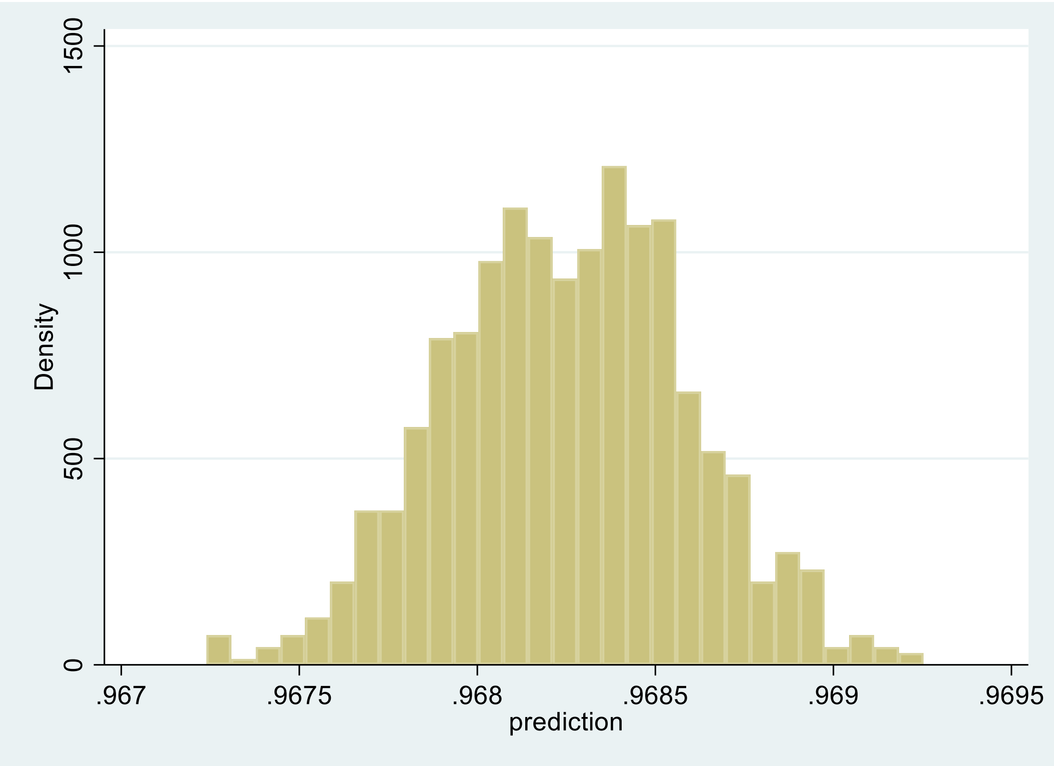
2014 Q03	-0.0773***
	(0.0224)
2015 Q01	-0.137***
	(0.0241)
2015 Q02	-0.278***
	(0.0241)
2015 Q03	-0.225***
	(0.0244)
2015 Q04	-0.283***
	(0.0242)
2016 Q01	-0.340***
	(0.0249)
2016 Q02	-0.393***
	(0.0223)
2016 Q03	-0.422***
	(0.0243)
2016 Q04	-0.491***
	(0.0251)
2017 Q01	-0.555***
	(0.0264)
2017 Q02	-0.559***
	(0.0268)
2017 Q03	-0.613***
	(0.0321)
2017 Q04	-0.679***
	(0.0305)
2018 Q02	-0.742***
	(0.0294)
2018 Q03	-0.817***
	(0.0332)
2018 Q04	-0.810***
	(0.0253)
2019 Q01	-0.832***
	(0.0333)
2019 Q02	-0.920***
	(0.0403)
change in quality of life	0.0166
	(0.0205)
change in safety score relative to average	0.0965
	(0.291)
change in housing score relative to average	0.667*
	(0.376)
change in amenities score relative to average	-0.104
	(0.235)
change in environmental score relative to average	0.111
	(0.185)
change in residents score relative to average	-0.653
	(0.402)
Constant	-0.0149
	(0.0105)
Observations	1,935
R-squared	0.730

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

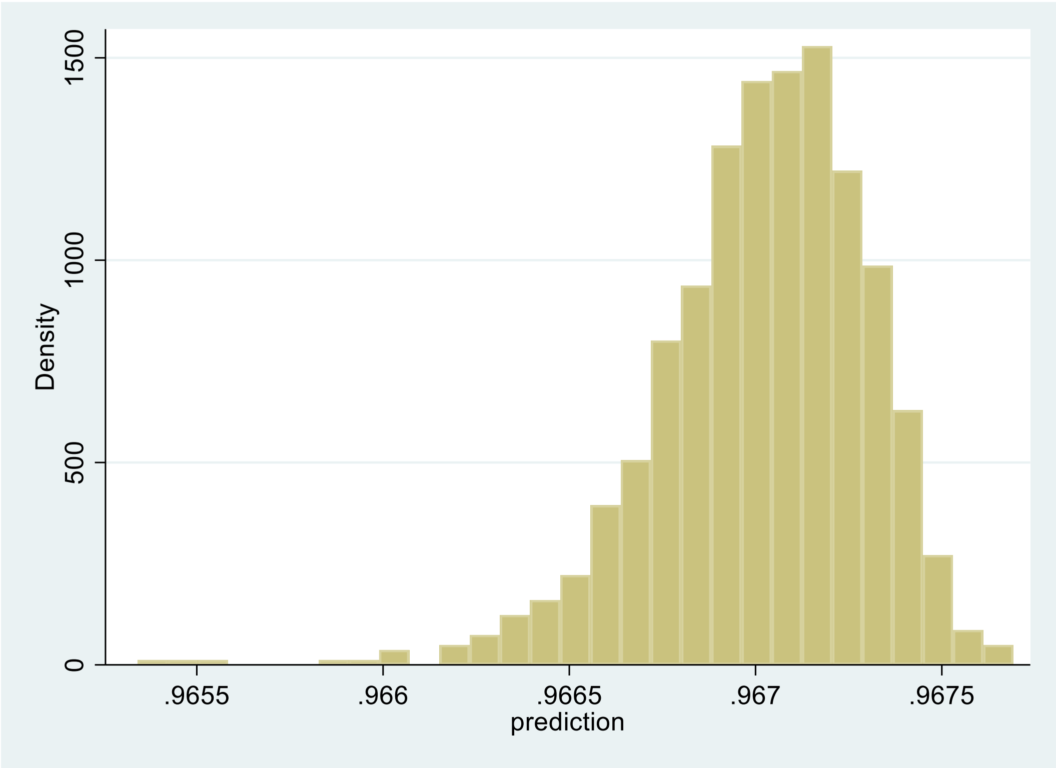
Appendix D – Robustness checks on our base model

We test our base model for robustness by splitting our sample in two equal proportions. We define a random variable (between 0 and 1) and select our data based on the value of this random variable (in sample if smaller than 0.5, out of sample if larger than or equal to 0.5. We run our base model based on the in sample subset and use this model to predict our dependent for the out of sample subset. We repeat this procedure 1000 times, while saving the results.

The histogram below shows our results, indicating in our view that the results are very robust.



In addition, we repeat this procedure by using just a small subset of our data (10 percent) for estimation, while predicting 90 percent. Based on selecting much smaller subsamples, the likelihood of obtaining differing results should increase. This yields the results below, which in our view also strongly support a robust base model. Again results are very robust to subsampling.


Density
0
500
1000
1500
.9655
.966
.9665
.967
.9675
prediction

Appendix E – Spatial heterogeneity of results

For an overview of the different districts see:
https://nl.wikipedia.org/wiki/Amsterdam_(gemeente)#/media/Bestand:Amsterdamse_stadsdelen_2010.png

Hedonic pricing model results:

Log of transaction price	(1) Centrum	(2) Nieuw-West	(3) Noord	(4) Oost	(5) West	(6) Zuid	(7) Zuidoost
Log of dwelling size (m2)	0.779***	0.592***	0.676***	0.792***	0.804***	0.781***	0.578***
	(0.00975)	(0.0121)	(0.0170)	(0.00967)	(0.00580)	(0.00780)	(0.0177)
No Airbnb's		0.0321***	0.0709				0.0245
		(0.0116)	(0.0523)				(0.0150)
Log of nr. of Airbnb's between 0 – 150 meters	-0.00668	-0.0126***	0.00929**	0.0173***	0.0176***	-0.00601*	0.0125**
	(0.00660)	(0.00279)	(0.00432)	(0.00343)	(0.00368)	(0.00319)	(0.00510)
Log of nr. of Airbnb's between 150 – 300 meters	0.0232**	0.00174	-0.0111***	-0.00246	-0.0170***	0.00518	-0.00164
	(0.0102)	(0.00271)	(0.00424)	(0.00447)	(0.00525)	(0.00419)	(0.00450)
Log of nr. of Airbnb's between 300 – 450 meters	0.00618	0.00444	-0.00756	-0.00630	0.0143**	-0.0185***	0.00613
	(0.0116)	(0.00294)	(0.00485)	(0.00523)	(0.00629)	(0.00480)	(0.00436)
Log of nr. of Airbnb's between 450 – 600 meters	0.0746***	-0.00602**	0.00160	0.00986**	-0.00971	-0.0182***	0.00212
	(0.0126)	(0.00287)	(0.00438)	(0.00429)	(0.00614)	(0.00480)	(0.00428)
Constant	8.759***	10.10***	9.830***	9.008***	8.752***	9.067***	9.285***
	(0.124)	(0.120)	(0.287)	(0.222)	(0.294)	(0.453)	(0.156)
Observations	5,501	5,271	3,473	6,797	9,784	10,245	2,058
R-squared	0.925	0.924	0.927	0.924	0.940	0.942	0.928

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

Repeat sales results:

% change in transaction price (w=0.025)	(1) Centrum	(2) Nieuw-West	(3) Noord	(4) Oost	(5) Zuid	(6) Zuid	(7) Zuidoost
% change dwelling size (m2)	0.735***	0.766***	0.911***	0.885***	0.943***	1.143***	0.0328
	(0.187)	(0.176)	(0.302)	(0.216)	(0.0818)	(0.274)	(0.237)
Airbnb emerging in neighborhood		-0.111*	0.218*				-0.165*
		(0.0574)	(0.126)				(0.0954)
% change in nr of Airbnb within 150 meters	0.00319	-0.00116	0.0143	-0.00149	0.0144*	0.0166	-0.00717
	(0.0132)	(0.00582)	(0.0137)	(0.00721)	(0.00854)	(0.0121)	(0.0163)
% change in nr of Airbnb within 150-300 mtrs	-0.0460	-0.00372	0.00415	-0.00409	-0.00989	0.0179**	0.0178*
	(0.0455)	(0.00531)	(0.00834)	(0.00911)	(0.00692)	(0.00897)	(0.00977)
% change in nr of Airbnb within 300-450 mtrs	-0.00525	-0.00291	0.00284	-0.00518	0.0327**	0.0158	-0.00433
	(0.0547)	(0.00648)	(0.0121)	(0.00827)	(0.0152)	(0.0126)	(0.0120)
% change in nr of Airbnb within 450-600 mtrs	-0.00664	0.00442	-0.00449	-0.00521	-0.0197	0.00224	0.0172
	(0.0578)	(0.00687)	(0.0119)	(0.00798)	(0.0200)	(0.00523)	(0.0119)
Constant	0.000667	0.0640	-0.0956	-0.00511	0.00509	-0.00392*	-0.0313
	(0.000884)	(0.0457)	(0.0754)	(0.00677)	(0.00535)	(0.00216)	(0.0901)
Observations	263	302	157	311	347	459	96
R-squared	0.668	0.830	0.805	0.850	0.828	0.766	0.934

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

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