AirBnB and The Housing Market

Team 16

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Abstract

We study the effect of the proliferation of AirBnB on residential property prices in Amsterdam. Using detailed data on property prices and AirBnB listings, we use several econometric approaches to show that the effects we estimate can be considered as causal. These include i) a hedonic regression framework, incorporating a double-lasso procedure to select the control variables with the most predictive power with regard to property prices and AirBnB proliferation, ii) a fixed effects model which exploits within-address and across-sale variation in AirBnB proliferation for a subset of properties which are sold multiple times and iii) an instrumental variables shift-share approach, merging external data from TripAdvisor.com, exploiting the fact that the interaction between the location of tourist amenities and Google searches exogenously predicts the spread of AirBnB listings. Across all three specifications, we find a small yet positive and significant effect of increased AirBnB listings on property prices, all of which are of a similar magnitude, adding weight to our claim of a causal effect. Specifically, we find that an increase of 100 AirBnB listings within 250 metres of a property causes the price of that property to increase by between 0.05 and 0.12%. Furthermore, we identify evidence of non-linear and heterogeneous effects.

Contents

1. Introduction

The price of houses in Amsterdam has increased exponentially over the past two decades. Sharing platforms such as AirBnB, as one of the worlds largest accommodation brands, has been identified as a potential culprit for the dramatic increase.

Identifying the causal effect of AirBnB proliferation on house prices is however difficult. First, it is possible that some unobserved characteristics of homes could be correlated with increased AirBnB proliferation. For example, demand for homes in more gentrified areas could be correlated with increased AirBnB lettings, making it difficult to separate the two factors. Second, the locations that AirBnBs establish themselves are likely not exogenous. Airbnbs are likely to appear in places deemed attractive to tourists, as tourists are the main consumers of these short term rentals.

We investigate the effect of AirBnB proliferation on house prices in Amsterdam using data on housing transactions in Amsterdam for the period 2000-2018 collected by the Dutch Board of Realtors and made available by their subsidiary Brainbay. Housing prices are traditionally modelled using hedonic regression methods. We begin by first investigating the effect of AirBnB density on housing prices using a hedonic model. An important challenge with this approach is, however, that we cannot account for unobserved heterogeneity, and cannot account for selection of AirBnBs into certain areas of Amsterdam. To address these issues we adopt two alternative approaches. First, we adopt a fixed effect model accounting for address of residence fixed effects. In this way we can account for unobserved heterogeneity at the dwelling level. To our knowledge we are the first to adopt such a method to investigate the causal effect of AirBnB on housing prices. This method, however, has its shortcomings. Namely, it does not permit us to address the issue of AirBnB selection into particular areas. It moreover means we need to limit ourselves to the sample of households that are sold more than once in the period 2000 to 2018, and for whom exposure to AirBnB changes. To account for this issue of selection into identification we use a novel re-weighting procedure. In addition to our address fixed effects approach we additionally adopt instrumental variable approach. This approach is inspired by the recent work of Barron et al. (2021) and Garcia-López et al. (2020) and involve the construction of an index of "touristyness" which we interact with trends in Google searches for the term "AirBnB Amsterdam". We find significant effects of AirBnB proliferation on house prices in Amsterdam, and the effect sizes are comparable across the three methodological approaches we adopt. Our preferred specification (using the instrumental variables approach) indicates that an increase of 100 AirBnBs within a radius of 250 meters of a household leads to a price increase of approximately 0.1 percent. We additionally investigate heterogeneity in the effect of AirBnB by size of dwelling (measured in terms of number of rooms) and time period following the introduction of AirBnB and find considerable heterogeneity in the effects, with dwellings with more rooms being more affected by AirBnB proliferation, and the effect of AirBnB on all dwellings being stronger in the six years following its introduction in 2008, compared to calendar years 2014 to 2018, suggesting an attenuation in the effects over time.

Our paper contributes to a small, but growing literature on the effects of AirBnb on housing prices (Barron et al., 2021; Garcia-López et al., 2020; **?**; Horn and Merante, 2017; Mindl, 2020; Koster et al., 2018). We contribute to this literature by being the first to investigate this question using actual address of residence fixed effects. We are moreover only the third to investigate the effect of Airbnb on house prices in the context of a large European city.

The rest of this paper proceeds as follows. In the following section we present our theoretical model for the effect of Airbnb density on house prices. This model then guides our subsequent analyses. In section 3 we describe the data used. In section 4 we present the methodology and results four our hedonic regression. In section 5 we present our methodology and results for our address fixed effects regressions. In section 6 we present our methodology and results for our instrumental variables approach and in section 7 we conclude and discuss policy implications of our findings.

2. Theoretical Context

To understand how short-term rentals via sharing platforms could potentially affect house prices, we follow the model by Garcia-López et al. (2020) in which house prices depend on owners choices to rent short- vs long-term and location choices of residents and tourists. From the model, we will gain hypotheses that we can test empirically in our analysis, guidance for our model selection and insights about potential threats to our identification strategies.

The set-up of the model by Garcia-López et al. (2020) is that a city consists of two neighborhoods, a city neighborhood c which is of a fixed size C and a suburb neighborhood s. Housing prices depend on the choices of owners to rent their properties either short term, receiving the annual rent T minus a cost b_j, or long-term, receiving an annual rent Q_c. This choice occurs because the traditional segmentation between short-term rentals to tourists and long-term rentals to residents diminished with the evolution of sharing-platforms such as AirBnB. The housing prices further depend on the choice of tourists and residents to reside in either one of the neighborhoods.

In the market-clearing equilibrium, the share of properties that are rented short-term b_j^* is given as follows:

$$b_j^* = \frac{(A_t - A_r) + C - \gamma(1-C)}{2C + (1-\alpha) + \gamma(C)} \tag{1}$$

with A_t and A_r being the valuation of the neighborhoods amenities by tourists and residents, respectively. This implies that the share of properties that are rented short term depends heavily on the difference between the tourists and the residents valuation of the amenities.

Finally, following Garcia-López et al. (2020) we model housing prices as a discounted cash flow of annual rents:

$$P^c = \sum_{t=1}^{\infty} \delta^t [(1-b_j^*]Q^c + \int_b^0 {}_j^*(T-b_j)db_j] \tag{2}$$

with the equilibrium price of long-term rents rising with the share of short-term rentals:

$$Q_c = (1 - C)(1 + \gamma) + A_r + (C + \gamma C - \alpha)b_j^* \quad (3)$$

This implies that housing prices are rising when the share of short-term rentals increases. The implications we gain from this model for our empirical analysis are as follows:

- The prediction of the model is that AirBnB activities in a neighborhood increase house prices, a hypothesis which we will test empirically.
- The model highlights that an important threat to our identification strategy is that AirBnB activities and the willingness to pay of local residents could move together and thereby simultaneously affect housing prices. This raises concerns to the identification of the causal effect of AirBnB on housing prices. We will address this problem in detail in our model selection.
- The model further predicts that AirBnB activities depend on amenities in the neighborhood, as they are differently valued by tourists and residents. We will test this prediction and exploit this observation using an instrumental variable approach.

3. Data

The analysis in this paper is based on one main dataset. The used dataset contains 108,441 observations about housing transaction prices in Amsterdam from 2000-2018 and was made available through Brainbay. The dataset includes the final transaction price (in €), information about the year of construction, the type (Apartment, Row house, Semi-detached house, Corner house, Two under one roof, Detached house) and the size of the house (size (measured in m^2), the volume (measured in m^3), and the number of rooms). Further, information is provided for whether a garden and/ or a parking spot is present, if the house is listed as a monument and a score about the general state of the quality. Additionally, we have data about the number of AirBnB listings within 250 metres of a property and the distance to the nearest AirBnB listing, also measured in metres. We identify and set to missing outliers in the volume and number of rooms variables, which affects 353 observations. The data comprise 108,088 properties.

In table 1 we present the descriptive statistics. The average house has 3 rooms and is around 86.667 m^2 large. Approximately 86.4 % are apartments, whereas only 0.3% are Semi-detached houses. 27.3% of the houses have a garden, while only 10% have a parking space available. Most of the houses were built between 1906-1930 (27.9%). The average sale price is 3.01e+05 €.

Our fig. 1 illustrates the massive growth of AirBnB listings in Amsterdam over the last decade. As AirBnB was founded in 2008, we find a strong increase of numbers of AirBnBs starting in 2008, interrupted by a short and sharp decrease in 2016. In fig. 2 we present the development of the transaction price from 2000 to 2018. It is evidently, that prices of houses in Amsterdam increased continuously. We observe a sharper increase of transaction prices starting around 2015.

4. Hedonic Regression

4.1. Method

Traditionally, house prices are modelled using hedonic regression models. In this method, the price of the final good is represented by the sum of the implicit prices of its components (Jones, 1988). Thus, in our first specification we estimate the following model:

$$log(P_i) = AirBnB_i + X_i + \epsilon_i \tag{4}$$

where the log price of house i depends on the number of AirBnB listings within 250m of the house, a vector of house characteristics X_i and a remaining error ϵ_i. We use the density of AirBnB listings around the property rather than the distance to the next AirBnB listing because density represents the overall AirBnB activity around a property which is the relevant determinant that affects house prices via an increased share of short-term rentals relative to long-term rentals as presented in section section 2. For ease of interpretation, we divide this variable by 100.

We select the variables to include in the vector X_i using the Lasso double selection method by Chernozhukov et al. (2015). Thereby, we perform Lasso regressions and test whether the selected variables are predictive of either our outcome variable, log house prices, or our treatment variable, AirBnB density. Those variables that prove to be predictive of either the log prices or AirBnB density are included in the hedonic price model and will also be included in all our subsequent models as control variables. As we discuss in section section 6.1 , we find clustering in assignment of AirBnB density at the zip-code level. Hence, we cluster standard errors at the zip-code level in all our specifications (Abadie et al., 2017).

The hedonic price method is, however, sensitive to omitted variable bias (Cropper et al., 1988). This means the estimates can be sensitive to unobserved house characteristics that are correlated with the AirBnB density and determinants of the house price. In addition, as we show in section (shift share), AirBnB density is not randomly assigned across the city but is in fact higher in touristy areas. House prices in touristy areas are likely to differ from house prices in other areas because of unobserved characteristics. All observable characteristics being equal, house prices in touristy areas might be higher because of gentrification processes (Garcia-López et al., 2020). On the other hand, house prices could be lower in touristy areas, everything else being equal, due to negative externalities such as noise and congestion. The estimates of the hedonic regression model would then be biased. For this reason, we acknowledge that the estimates from this specification should be interpreted descriptive rather than causal. The results from this regression should therefore be seen as a baseline for comparisons with subsequent specification models.

Furthermore, the hedonic regression cannot remove the issue of selection of AirBnBs into different areas of the city. Specifically, AirBnBs listings may be more likely to occur in areas near the city centre, as tourists generally prefer to locate themselves as close to the centre of a city as possible. Additionally, the growth of AirBnB occurred in parallel to the recovery from the global financial crisis. If areas of high demand for tourists are also areas of high real estate demand in general and of areas where demand recovered faster after the crisis, then our estimates will be biased up since increased AirBnB density is also correlated with other demand.

4.2. Results

In table 2 we present our results from estimating eq. (4). In column (1), we regress the log price against the density of AirBnBs without controls, and in column (2) and (3) we add different sets of control variables. Across all specifications, our coefficients are positive and highly significant. The estimate presented in column (1) indicates that an increase of 100 AirBnB listings within 250m is associated with an increase in the house price of 0.142 percent. Including different sets of control variables decreases the effect size to 0.051 percent with all controls included and 0.126 percent with the lasso-selected controls included. The fact that the effect size increases considerably when we only control for the lasso-selected variables, which might be a sign of overcontrolling in column (2). In column (4), we include the squared density of AirBnB listings to test for non-linear effects. The negative and significant coefficient of -0.05 indicates that the effect of AirBnB listings on house prices is positive, but diminishing at higher levels of AirBnB density.

5. Address Fixed Effects

5.1. Method

As discussed above, hedonic regressions cannot truly remove the issue of omitted variable bias. In order to address this problem, we exploit the fact that many properties in our data are sold on multiple occasions in a fixed effects set-up. By including address fixed effects in our model, we are able to leverage within-address, across-sale variation in AirBnB density to identify the effect of increased saturation of AirBnB listings on sales prices. We therefore estimate the following equation:

$$log(P_{it}) = AirBnB_{it} + \gamma_i + \delta_t + X_i t\beta + \epsilon_i \tag{5}$$

where $log(P_{it})$ is the log sales price of address i at sale t, $AirBnB$ represents the number of AirBnB listings within 250 metres of an address, divided by 100 and γ and δ are address and time fixed effects, respectively. $X_i t$ a subset of our lasso-selected control variables, which may change over time, and we cluster standard errors at the 4-digit postcode level.

While this approach removes any omitted variables bias at the address level, biases may still arise due to selection in two ways. First, there may be selection in the types of properties which are sold multiple times. For example, as will be discussed in section 6.1, AirBnB density is higher in areas with more tourist amenities, which correspond to areas in and around the city centre. If homes near the city centre are more likely to be traded as investments, the effects of AirBnB saturation may be lower for these homes, biasing down our estimates. To deal with this issue, we follow Miller et al. (2019), who suggest a re-weighting procedure to adjust for selection into fixed effects panels. Specifically, we estimate a probit model, predicting the propensity of each address to appear in our data more than once. We estimate this propensity as a function of our lasso-selected control variables, the price of a property's first sale and its year of first sale, as properties sold for the first time in more recent years have less time to re-appear in our data.

A second source of selection bias is that it cannot remove the issue of selection of AirBnB listings into an area, as discussed in section section 4.1. A further downside of this methods is that, as we identify within-address variation in AirBnB density, we are not able to identify non-linear effects as density is de-meaned at the address-level and non-linear effects would be identified at different levels of AirBnB density, which would cause inconsistency in our estimates.

5.2. Results

The table 3 presents our results from estimating equation eq. (5) including different sets of control variables. Across all specifications, the coefficient of AirBnB density is positive and significant. In column (1), we estimate the model only including time and address fixed effects, without any further controls. Our results indicate that an increase of 100 AirBnB listings within 250m of a house leads to an increase in the house price of 0.143 percent. This effect size is almost identical to the effect estimated with the hedonic regression model without controls, indicating that omitted variable bias is not a major concern here. Including the lasso-selected control variables, the effect size is reduced to 0.051 percent. To test if selection into multiple sales could be a concern, we present the results from estimating the propensity for multiple sales in table A1. The results show that almost all characteristics do significantly affect the probability for multiple sales. For example, the type of the house is a predictor of multiple sales, with apartments being more likely to be sold multiple times than other house types and more recently built houses being less likely to be sold several times. We present the coefficients for the regression of eq. (5) with the corresponding re-weighted fixed-effects in column (3) of table 3. The coefficient for AirBnB density is almost identical to the estimate in column (2), suggesting that selection into multiple sales is no major concern here.

6. Shift-Share Instrument

6.1. Method

To tackle the endogeneity of Airbnb location, we follow Barron et al. (2021) and Garcia-López et al. (2020) in using a shift-share instrument that combines the following: i) cross-sectional variation in the location of tourist amenities across addresses and ii) the aggregate time-variation in AirBnB activity. The composition of an IV, using the combination of a potentially endogenous cross-sectional exposure variable and a plausibly exogenous time-varying variable , was first suggested by Bartik (1991) and is increasing in popularity. For our cross-sectional "share" component of the instrument, we construct an index of the "touristy-ness"of an address.

Our instrument aims to capture the set of amenities that tourists appreciate while not being of particular interest to residents. We produce a list of the Amsterdam's tourist amenities and collect the number of reviews of each tourist attraction, using data from TripAdvisor.com.

To determine the measure of tourist amenities we use the following approach:

$$\text{Tourist Amenities}_{\,i} = \sum_k \frac{1}{\text{dist}_{\,i,k}} \times \text{ Reviews}_{\,k} \tag{6}$$

where k denotes the amenity, $dist_{n,k}$ is the distance in meters between the address n and the amenity k. $Reviews_k$ indicates the number of of TripAdvisor Reviews.

Coming to the "shift" part of our instrument, we follow Barron et al. (2021) and Garcia-López et al. (2020) by using worldwide searches in Google for "AirBnB Amsterdam". This data is normalised to a 0-100 scale, with 100 representing the month with the highest number of searches. The variable is measured at the monthly level.

The intuition behind our used shift-share instrument is the following: the touristy-ness of an address predicts the location of the AirBnB listings, while Google searches for the term 'AirBnB Amsterdam' predicts the time period when the listings appear. In order for our instrument to be valid, it must necessarily be uncorrelated with address-specific time-varying shocks to the housing market. Our instrument is only allowed to be correlated to the transaction price through its effect on AirBnB listings. Specifically, in areas with AirBnB listings, we should see a positive relationship between the instrument and the transaction prices. Whereas we should not observe a positive relationship between the instrument and the transaction prices in areas with few or no AirBnB listings. Furthermore, we argue that our instrument is exogeneous, since it is relatively unlikely that inhabitants' preferences to locate close to tourist attractions changed during the period 2000–2018 for reasons other than tourism. Barron et al. (2021) investigate the validity of a similar instrument extensively in the context of the United States housing market and argue that it is a valid instrument.

As such, we estimate the following system of equations:

$$log(P_i) = \beta Air\hat{B}nB_i + \epsilon_i \tag{7}$$

$$Air\hat{B}nB_i = \alpha + \gamma TouristAmenities_i * G_t + \varepsilon_i \tag{8}$$

where $log(P_{it})$ is the log sales price of property i, $AirBnB$ represents the number of AirBnB listings within 250 metres of an address, divided by 100. $TouristAmenities$ represents the touristy-ness index of a property and G_t represents the trend in google searches for "AirBnB Amsterdam" during the month of sale t. We again cluster standard errors at the 4-digit postcode level. While we are unable to identify non-linear effects in an IV framework (), we use this model to identify heterogeneities in the effect of AirBnB on prices.

6.2. Results

In table 4 we present both first stage and reduced form results of these analyses. The F-statistic of our instrument is 30.25, indicating that our instrument is relevant for this analysis (Angrist and Pischke, 2008). Our first stage results indicate that the instrument is strongly predictive (at the 1% significance level) of AirBnB density. This implies that there does in fact exist strong selection of AirBnB listings across the city of Amsterdam, with listings more likely to appear in more toursity areas at times when demand is high. While this could call into the question the results presented in section 4.2 and section 5.2 due to the presence of selection bias. However, as the effects we identify using our shift-share instrument are similar in magnitude to those previously identified, we believe that our identification strategies can still be considered causal.

The reduced form results also suggest that the instrument is strongly predictive of the log of sales price. The coefficient on the instrument in the reduced form regression is moreover very similar to the coefficient on AirBnB density in of our hedonic regression without controls (table 2, column 1) as well as the coefficient on AirBnB density in our address fixed effects analysis without controls. Moving on to our IV 2SLS results, when we do not include controls, we find that an increase of 100 AirBnB listings within a radius of 250 meters of a household increases the sale price of that home by 0.296 percent. This estimate does not, however include controls for unobserved heterogeneity that is constant at the four-digit postcode level over time, or unobserved heterogeneity that is constant across all postcodes but changes over time. When including calendar year-month and postcode fixed effects, our estimate is reduced to 0.096 but remains significant at the 1 percent level. When we additionally include controls selected by the Lasso double selection method, the effect remains significant and reduces only slightly in magnitude to 0.077. This estimate of 0.077 percent is comparable to our estimates in the address fixed effects analyses with controls (both the standard version and using the re-weighting method proposed by (Miller et al., 2019)), though considerably smaller than the effects estimated in our hedonic regressions when including covariables selected by the Lasso double selection method (Chernozhukov et al., 2015).

6.2.1. Heterogeneity

It is possible that the effect of AirBnB differs by house type or size, or that the effects of AirBnB density change over time as the market becomes more saturated. We investigate whether the effect of AirBnB on house prices differs by the number of rooms a household has, comparing households with four or more rooms compared to those with three or less, and between the six-year period immediately following the entry of AirBnB compared to next five years. We believe these are interesting splits to make in the sample because the City of Amsterdam has a rule that it is illegal to rent out to more than four tenants simultaneously.[1] We find that the effect of Airbnb is considerably larger in the first period following the entry AirnBnb to the short-term

[1] `https://www.amsterdam.nl/wonen-leefomgeving/wonen/vakantieverhuur/vergunning/`

rental market (see table 5) and tapers off, but remains significant at the 5 percent level. Overall, in the first period, an increase of 100 Airbnbs within a 250 meter radius leads to an increase in house price of 0.222 percent. In the period 2014-2018 an increase in Airbnb density of the same amount leads to an increase in house prices of 0.102 percent. This translates into an increase of approximately 28,400 Euro in the sale price of the average dwelling in 2014.

The effect of AirBnB is also significantly different for dwellings with three rooms or less compared to those with four rooms or more, with the effect size for dwellings with four rooms or more nearly double that for dwellings with three rooms or less. This is interesting considering the above-mentioned rule forbidding renting to more than four tenants simultaneously. Anecdotally, it seems, however, that this rule only became salient to many AirBnB hosts in January 2017 [2]. It is thus possible that potential hosts invested in large properties to rent out without knowing about this regulation.

7. Conclusion and Discussion

The question of how the sharing economy affects all of our lives has grown enormously in recent years. To to fore of this discussion has been the effect of AirBnB and other home-sharing platforms on housing markets in large cities and Amsterdam is no exception. It is therefore of interest to examine whether and how the increasingly large presence of AirBnB affects the market for residential properties.

In this paper we have presented a basic theoretical model outlining how short-term rentals affect residential property prices. In short, our model predicts that an increase in the proliferation of AirBnB leads to increased demand for short-term letting, reducing the supply of long-term lettings, which in turn increases demand for home purchases, pushing up prices in turn. However, identifying these causal effects is difficult in practice. This could be due to unobserved characteristics of homes which could be correlated with AirBnB listings and simultaneously affect prices but also due to the selection of AirBnB lettings into areas with different trends in home prices.

To deal with the former issue we employ two strategies. First, we use of a hedonic regression to control for as many observed factors affecting prices as possible. Second, we use an address fixed effects strategy, for a subset of address sold multiple times, to remove any unobserved time-invariant property characteristics. the deal with the latter issue, we use a shift-share instrument, leveraging the interaction between the time-varying demand for AirBnB (the shift) and the touristy-ness of an address (the share), to identify plausibly exogenous variation in the spread of AirBnB listings.

Across all model specifications, we find small yet positive and significant effects of AirBnB density on housing prices in Amsterdam. We find that the effect sizes are of similar magnitude across all specifications, which adds weight to our claim of identifying causal effects. With this result, we empirically tested the predictions arising from the theoretical model and confirm the prediction of a positive effect of AirBnb density on housing prices. We also find evidence in favour of the prediction

[2] https://community.withairbnb.com/t5/Hosting/Some-news-on-how-Airbnb-will-now-have-to-enforce-existing/m-p/272415/highlight/true#M64239

that AirBnB activities depend on amenities in the neighbourhood. Furthermore, we find evidence of a decreasing effect of AirBnB over time, consistent with the concept of a decreasing marginal effect, and we find larger effects of AirBnB proliferation on prices for homes with more rooms.

With regard to policy implications, the effects we identify are rather small and cannot explain the bulk of the enormous increases of housing prices in Amsterdam in recent years. Specifically, we identify that an increase of 100 AirBnB listings within 250 metres of a property lead to a increase in prices of between 150 euros and 361 euros of the mean price. Among the public and policy makers, the consequences of AirBnB for the housing market have been a large concern in recent years. This has led to the implementation of a wide range of regulations, for example Amsterdam has reduced the number of maximum stays per AirBnb to 30 nights per year as of January 2019 and even abolished AirBnB in three neighborhoods in the city in 2020. Our results indicate that the effect of AirBnB on house prices are rather small and do not explain the bulk of the increase in recent years. Furthermore, we find evidence that effects of AirBnB on prices are decreasing over time, perhaps implying that in the coming years, AirBnB will become a smaller determinant of prices.

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8. Tables and Figures

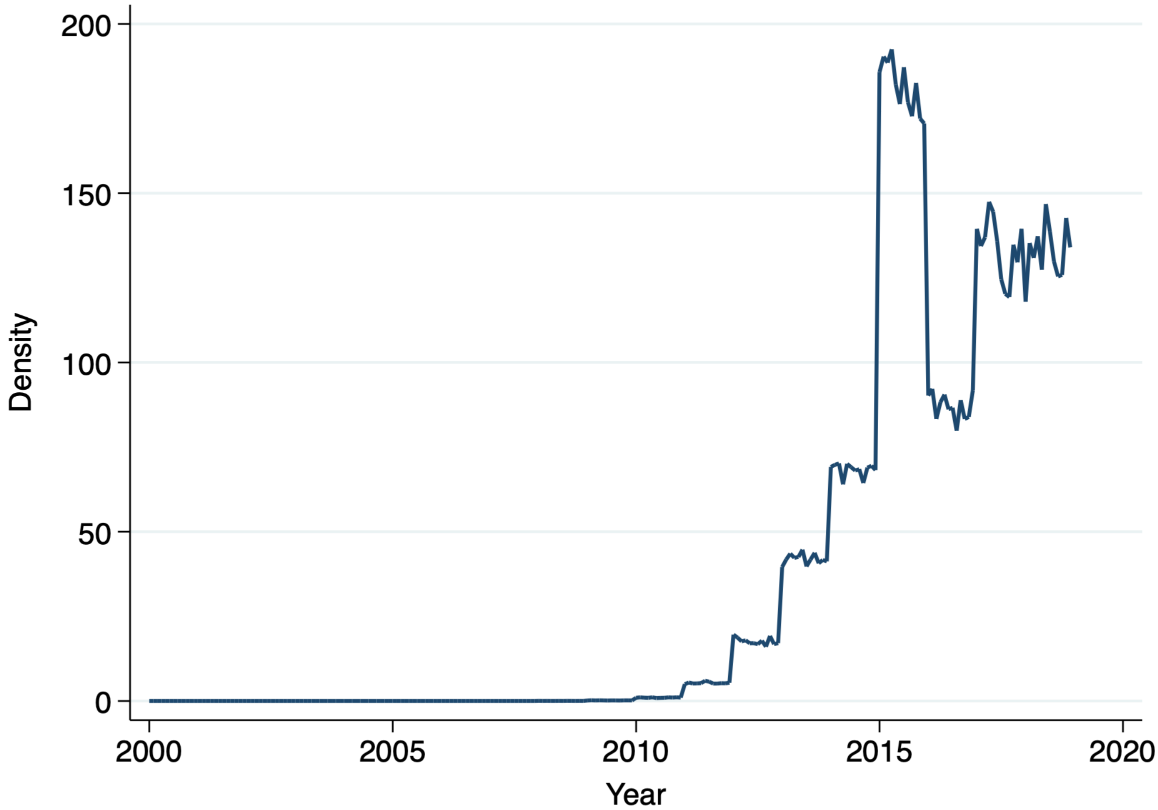

Figure 1: Airbnb growth in Amsterdam.
Notes: This graph plots the average number of AirBnB listings within 250m from 2000 to 2018 in Amsterdam per month.

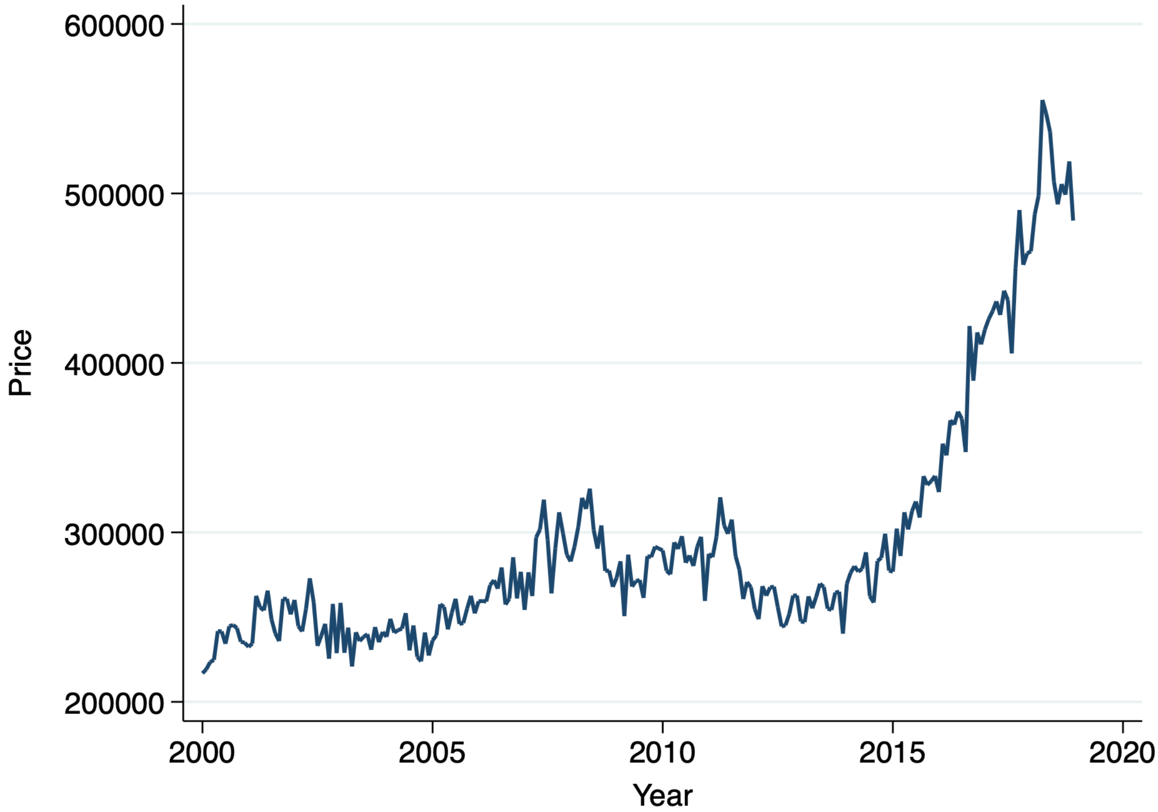

Figure 2: House price.

Notes: This graph plots the average transaction price from 2000 to 2018 in Amsterdam per month.

Table 1: Descriptive statistics.

	(1)				
	Mean	Sd	Min.	Max	Obs.
Final transaction price	301,044	228,107	50000	2,500,000	108,441
Garden present	0.273	0.446	0.000	1.000	108,441
Parking available	0.104	0.305	0.000	1.000	108,441
Status as a monument	0.031	0.174	0.000	1.000	108,441
Buyers cost or free	1.036	0.187	1.000	2.000	108,441
Size in m^2	86.667	42.957	25.000	1185.000	108,441
Volume of house in m^3	242.558	126.937	55.000	1000.000	108,088
Number of rooms	3.246	1.331	0.000	16.000	108,437
Apartment	0.864	0.343	0.000	1.000	108,441
Row house	0.091	0.288	0.000	1.000	108,441
Semi-detached	0.003	0.054	0.000	1.000	108,441
Corner house	0.025	0.158	0.000	1.000	108,441
Two under one roof	0.008	0.089	0.000	1.000	108,441
Detached house	0.008	0.090	0.000	1.000	108,441
1500-1905	0.151	0.358	0.000	1.000	108,441
1906-1930	0.279	0.449	0.000	1.000	108,441
1931-1944	0.091	0.287	0.000	1.000	108,441
1945-1959	0.050	0.217	0.000	1.000	108,441
1960-1970	0.099	0.298	0.000	1.000	108,441
1971-1980	0.040	0.196	0.000	1.000	108,441
1981-1990	0.107	0.309	0.000	1.000	108,441
1991-2000	0.121	0.326	0.000	1.000	108,441
>=2001	0.063	0.243	0.000	1.000	108,441
General state of quality of the house, score	14.395	1.766	2.000	18.000	108,441
Number of Airbnb listings within 250m	44.000	90.553	0.000	685.000	108,441
Distance to nearest Airbnb listing	274.718	882.637	0.000	8842.936	108,441

Notes: This table contains descriptive statistics. The data was made available through Brainbay. The covered time period ranges from 2000 to 2018.

Table 2: Hedonic Regression Results

	(1)	(2)	(3)	(4)
AirBnB density	0.142***	0.051***	0.126***	0.321***
	(0.017)	(0.007)	(0.015)	(0.039)
(AirBnB density)^2				–0.050***
				(0.008)
N	108,441	108,084	108,088	108,088
Controls	None	All	Post-Lasso	Post-Lasso

Notes: Robust standard errors, clustered by 4-digit zip code, in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

Table 3: Address Fixed Effects Results

	(1) FE	(2) FE + Controls	(3) Re-weighted FE
AirBnB density	0.143***	0.051***	0.052***
	(0.015)	(0.010)	(0.011)
Controls	None	Post-Lasso	Post-Lasso
N	52,080	52,080	51,998

Notes: Robust standard errors, clustered by 4-digit zip code, in parentheses. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

Table 4: Shift-Share Instrument Results

	(1) 1st Stage	(2) Reduced Form	(3) IV	(4) IV	(5) IV + controls
Dep. Var.	Density	Ln(Price)	Ln(Price)	ln(Price)	ln(Price)
Instrument	0.580***	0.172***			
	(0.105)	(0.028)			
AirBnB density			0.296***	0.096***	0.077***
			(0.025)	(0.018)	(0.013)
Controls	None	None	None	Month, Zip Code	Post-Lasso
N	108,441	108,441	108,441	108,441	108,084

Notes: Robust standard errors, clustered by 4-digit zip code, in parentheses. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

Table 5: Shift-Share Instrument - Heterogeneity

	(1) 2008-2013	(2) 2014-2018	(3) >= 3 Rooms	(4) >= 4 Rooms
AirBnB density	0.222***	0.102**	0.058***	0.104***
	(0.037)	(0.047)	(0.014)	(0.013)
Mean Price	265,804	370,206	240,543	425,246
N	71,599	36,485	72,892	35,192

Notes: Robust standard errors, clustered by 4-digit zip code, in parentheses. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

Appendix A.

Table A1: Propensity for multiple sales

	(1) Pr(≥2 Sale)
Year of 1st sale	–0.133***
	(0.001)
ln(Price of 1st sale)	–0.171***
	(0.017)
Row house	–0.329***
	(0.019)
Semi-detached house	–0.082
	(0.082)
Corner house	–0.332***
	(0.030)
Two under one roof	–0.437***
	(0.053)
Detached house	–0.351***
	(0.055)
Built 1500-1905	0.026
	(0.023)
Built 1906-1930	0.099***
	(0.021)
Built 1931-1944	0.102***
	(0.024)
Built 1945-1959	–0.106***
	(0.028)
Built 1960-1970	–0.118***
	(0.024)
Built 1971-1980	–0.302***
	(0.029)
Built 1981-1990	–0.214***
	(0.023)
Built 1991-2000	–0.110***
	(0.022)
Garden	–0.042***
	(0.012)
Size (m^2)	–0.005***
	(0.000)
Volume (m^3)	0.001***
	(0.000)
Rooms	0.012**
	(0.005)
Parking	–0.161***
	(0.017)
Monumental status	0.141***
	(0.025)
Buyer pays or fee	–0.404***
	(0.024)
Quality index	0.015***
	(0.003)
N	108,084

Notes: Robust standard errors, clustered by 4-digit zip code, in parentheses. * p<0.10 ** p<0.05 *** p<0.01.