House-tile takeover? The effects of home-sharing on the Amsterdam housing market

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Abstract

We study the effect of AirBnB on housing prices in Amsterdam, using several econometric approaches to show that these effects have a causal interpretation. These include i) a hedonic regression model, incorporating a double-lasso procedure to select control variables, 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 these specifications, we find a positive and significant effect of AirBnB listings on prices. 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 5 and 12%. Furthermore, we identify evidence of non-linear and heterogeneous effects. In a broader market equilibrium analysis, we identify that the increase in house prices is driven by an increase in asking prices. Furthermore, using an instrumental variables approach to incorporate the causal effect of asking prices into our model, we find that asking prices and AirBnB density affect sales prices simultaneously, while we find no effects on sales volume or time on the market.

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1. Introduction

The price of houses in Amsterdam has increased exponentially in recent years. The rapid growth of AirBnB, a platform that allows individuals to rent out their homes on a short-term basis, has coincided with this dramatic increase. This has lead policy-makers to wonder whether home-sharing business models have been partly to blame for the explosion in prices.

Identifying the causal effect of AirBnB proliferation on house prices is 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. This would make it difficult to separate the two factors and identify the causal effect of AirBnB. Second, we have a selection issue in that 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 identify the causal effect of AirBnB on residential property prices using three identification strategies. These are: i) a hedonic regression framework, incorporating a double-lasso procedure to select the control variables with the most predictive power with regards 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 that are sold multiple times. This approach removes any omitted variables bias remaining in the hedonic model. iii) An instrumental variables shift-share approach, merging external data from TripAdvisor.com on tourist amenities and Google search trends, exploiting the fact that the interaction between the location of tourist amenities and Google searches exogenously predicts the spread of AirBnB listings. This approach serves to remove any biases caused by the selective locations of AirBnB listings. Furthermore, in a broader market equilibrium analysis, we investigate the relationship between AirBnB, asking prices, time on the market and final sales prices. Adopting a further instrumental variables approach, we identify the causal effect of asking price on time on the market and final sales price.

We find significant effects of AirBnB proliferation on house prices in Amsterdam. The effect sizes are of a similar magnitude across all of our identification strategies, confirming the robustness of our results. In our preferred specification, using the instrumental shift-share approach, we estimate that an increase of 100 AirBnBs within a radius of 250 meters of a household leads to a price increase of approximately 8%. This corresponds to an increase of €24,000 on the mean price. We investigate heterogeneity in the effect of AirBnB by dwelling size (measured in terms of number of rooms) and time period following the introduction of AirBnB. We find considerable heterogeneity in the effects of size of dwelling, with the effect on dwellings of four or more rooms being almost twice as large as the effect on dwellings with three rooms or less (5.8% versus 10.4%). We moreover find that the effect of AirBnB density on the price of all dwellings was relatively similar in the periods 2008-2014 and the more recent period 2017-2018.

In our market equilibrium analysis, we find that neither asking prices nor AirBnB density have a significant effect on length of time on the market or sales volumes. This suggests that the housing market in Amsterdam is efficient. We find that asking prices are closely related to final sales prices, with a 1% increase in asking price leading to an approximately 0.6% increase in sales price. Asking price is a stronger predictor of final sales price than AirBnB density, but AirBnB density remains a strong and economically significant predictor of sales price (effect size 3%) when asking price is accounted for.

The rest of this paper proceeds as follows. In section 2 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 for our three identification strategies used to establish the causal effect of AirBnB on house prices, and additionally investigate heterogeneity in these effects. In section 5 we conduct a market equilibrium analysis, investigating the effect of AirBnB density on transaction volumes and the relationship between asking prices, sales prices and time of the market. In section 6 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.

In the Garcia-López et al. (2020) model, a city consists of two neighbourhoods, a city neighbourhood which is of a fixed size C and a suburb neighbourhood 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 of 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. Housing prices further depend on the choice of tourists and residents to reside in either one of the neighbourhoods.

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

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

where A_t and A_r represent a valuation of the neighbourhood's 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:

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

in which long-term rentals are obtained from inserting the market clearing condition from eq. (1) into the marginal resident's willingness to pay function. We follow Garcia-López et al. (2020) and model the residents willingness to pay function as $Q^c(e_{ir}^*) = A_r - \alpha\ F_b(b_j^*) + e_{ir}^* + Q^s$, where $\alpha\ F_b(b_j^*)$ reflects the negative externality arising from tourism and e_{ir}^* reflecting the residents preference to live in neighbourhood c instead of neighbourhood s. The equilibrium price of long-term rents is thus given as follows:

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

The predictions of eq. (1) to eq. (3) are thus that an increase in AirBnB density leads to an increase in the supply of short term rents, coinciding with an decrease in the supply of long-term rents. This increases the price of long-term rents, making property investments more attractive to prospective buyers, thereby leading to increased sales prices.

The model of the transaction processes in the housing market suggested in Dubé and Legros (2016) allows us to predict potential mechanisms underlying this effect. In their model, the final sales price is determined as the result of a two-step process. First, the seller lists the asking price. In the second step, both the final sale price and the time on the market are determined simultaneously in the negotiation process between the seller and the buyer, which depends on the motivation of both agents. Increasing AirBnB density in a neighbourhood constitutes a demand shock to the housing market. In an efficient market, this demand shock will translate into increased sales prices. Assuming sellers are rational agents, they will incorporate higher price expectations in their listing prices, increasing asking prices to the same extent. Given that housing supply is inelastic, this upward shift in demand will lead to increased prices but will have a minimal effect the quantity demanded or supplied. The time on the market will thus be unchanged.

Overall, the implications we gain from this model are as follows:

- Greater AirBnB activity in a neighbourhood increases house prices, with asking prices increasing to the same extent. Moreover, a model of an efficient, inelastic housing market predicts that an increase in sales prices does not significantly affect the transaction volume of house sales or time on market.

- 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 for the identification of a causal effect of AirBnB on housing prices.

- The model further predicts that AirBnB activities depend on amenities in the neighborhood, as they are differently valued by tourists and residents.

Testing these hypotheses empirically is challenging for at least two reasons. First, we face the threat of omitted variable bias. Houses and neighbourhoods with different AirBnB densities are likely to differ also with respect to other characteristics that are correlated with house prices. For example, AirBnB density might be higher in areas with a high degree of gentrification, for which residents have a higher willingness to pay which leads to higher house prices. Those factors could be unobserved to the econometrician and therefore difficult to control for. As a result, it is insufficient to just compare houses in areas with high and low AirBnB densities.

Second, we potentially face selection bias. This is a direct implication of the above drafted model, in which we showed that tourists and residents value local amenities differently. Hence, AirBnB listings may be more likely to occur near the city centre, where house prices may increase at a different trajectory to those in more suburban areas for other reasons than the spread of AirBnB. Just comparing houses in areas with different AirBnB densities might thus bias the estimates.

Ideally, we would like to identify the causal effect in an experimental set-up in which AirBnB densities within 250 meters are randomly assigned to otherwise identical houses. This would allow us to isolate the causal effect of AirBnB activity on house prices. Such an experiment is, however, not feasible in practice as AirBnB density cannot be randomly assigned since it is the result of numerous individual choices by house owners and prospective tenants and tourists. Moreover, it would not be possible to find an adequate sample of identical houses within Amsterdam that one could assign AirBnB densities. In the remaining parts of the paper, we will discuss in detail how to overcome these potential sources of bias and suggest different identification strategies that allow us to estimate the causal effect of AirBnB density on house prices.

3. Data

The analysis in this paper is mainly based on one dataset provided with the case. The data contains 108,441 observations about housing transaction prices in Amsterdam from 2000-2018 and was made available via Brainbay. The data include the final transaction price for each sale (in €), the asking price (in €), the time on the market (in days), 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.

In table 1 we present the descriptive statistics. The average house has 3 rooms and is around 86.667 m^2 in size. 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 €301,044, while the average asking price is slightly higher with €310,463. In Amsterdam a house spends approximately around 117 days on the market.

In fig. 1, we illustrate the rapid 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. At the end of 2014, AirBnB and the city of Amsterdam signed an agreement that AirBnB would provide hosts with improved information on the rules for home sharing and to simplify the processing of tourist taxes, making it simpler for AirBnB hosts. As can be seen, this led to a sharp increase in the number of listings in 2015, although this growth slowed somewhat in further years. In fig. 2 we present the development of the transaction and the asking price from 2000 to 2018. It is evident that the existing gap between the transaction and the asking prices of houses in Amsterdam has been decreasing in recent years, particularly from around 2015. Further, for reason of comparison we add the Consumer price index (2010=100) our graph. Clearly, the increase in the presented house prices is steeper as for the consumer price index in the Netherlands.

4. Reduced Form Effects on House Prices

4.1. Hedonic Regression

4.1.1. Method

Traditionally, property prices are modelled using hedonic regression models. In this method, the price of a property is estimated as 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 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 4.3.1 , 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 4.3.2, 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 as 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.

4.1.2. 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 14.2%. Including different sets of control variables decreases the effect size to 5.1% with all controls included, while including only lasso-selected controls increases the effect size to 12.6%. The fact that the effect size increases considerably when we only control for the lasso-selected variables indicates that including all of the control variables in column (2) causes over-fitting, removing variation in the density variable and biasing the results downward.

In column (4), we include the squared density of AirBnB listings to test for non-linear effects. As the coefficient on density increases significantly and the coefficient on the quadratic term is negative and significant, this indicates that the effect of AirBnB listings on house prices is positive, but diminishing at higher levels of AirBnB density.

4.2. Address Fixed Effects

4.2.1. 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 4.3.1, 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 4.1.1. 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.

4.2.2. Results

The table 3 presents our results from estimating 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 14.3% 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 5.1% 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. In addition, more expensive homes and larger homes are less likely to be sold multiple 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 not a major concern in this case.

4.3. Shift-Share Instrument

4.3.1. 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, $dist_{i,k}$ is the distance in meters between the address i 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 (Mogstad and Wiswall, 2010), we use this model to identify heterogeneities in the effect of AirBnB on prices.

4.3.2. 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 touristy areas at times when demand is high. While this could call into the question the results presented in section 4.1.2 and section 4.2.2 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 29.6% 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 9.6% but remains significant at the 1 percent level. When we additionally include controls selected by the Double-Lasso selection method, the effect remains significant and reduces only slightly in magnitude to 0.077. This estimated effect of 7.7% 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 lasso-selected covariates.

4.3.3. 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 four years, split into periods of two. 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 to more than four tenants simultaneously, potentially making dwellings of four rooms or more less attractive as AirBnB rental properties.[1] We choose our particular time period split for investigating heterogeneity for two reasons. First, in December 2014 AirBnB and the City of Amsterdam agreed that AirBnB would make the rules for homesharing in the city clearer and simplify the process for the payment of tourist taxes by hosts[2]. These two changes thus made it easier for potential AirBnB hosts to start operating in the city. Second, AirBnB and the City of Amsterdam agreed in December 2016 that AirBnB would automatically cap the number of nights that hosts are allowed to rent out their entire homes to 60(Almagro and Domınguez-Iino, 2019). The policy of not being allowed to rent out one's entire home for more than 60 nights in a calendar year had been in place previously, but only weakly enforced. Enforcing this rule directly through the AirBnB platform made it more difficult to get around. It is thus possible that investing in properties with the intention of renting them on AirBnB became less attractive in the post-2017 period.

We find that the effect of AirBnB on house prices is strong and significant in the six-year period following the entry AirnBnB to the short-term rental market (see table 5). We estimate a very large, but non-significant effect in the second period (2015-2016). In the third period the effect size is similar to that estimated for the first six year period following the introduction of AirBnB, but is only significant at the 10% level. This may be a power issue considering we "only" have observations on 11,637 homes sold, multiple controls and fixed effects for both four-digit post-code and month-year. Overall, in the first period, an increase of 100 AirBnBs within a 250 meter radius leads to an increase in house price of 23.4% percent and in the period 2017-2018 an increase in AirBnB density of the same amount leads to an increase in

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

[2] https://www.airbnb.es/press/news/amsterdam-and-airbnb-sign-agreement-on-home-sharing-and-tourist-tax

house prices of 24.5% percent. The unstable result in 2015-16 is potentially due to the dramatic readjustment in AirBnB listings observed in the period 2015-2016 (see fig. 1).

The effect of AirBnB is 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 fewer rooms. This is interesting considering the above-mentioned rule forbidding rentals to more than four tenants simultaneously. Anecdotally, it seems, however, that this rule only became salient to many AirBnB hosts in January 2017 [3]. It is thus possible that potential hosts invested in large properties to rent out without knowing about this regulation.

5. Market Equilibrium Analysis

There likely exist several mechanisms underlying the positive effect of AirBnB on house sales prices identified in the previous sections. In the following sections we take a broader look at how AirBnB has affected the market equilibrium. Specifically, we examine the effect of AirBnB density on transaction volumes and asking prices. Furthermore, we exploit an instrumental variables approach to incorporate the causal effect of increased asking prices into our model, examining how AirBnB density and asking prices simultaneously determine the time a property spends on the market and final sales prices.

5.1. Transaction volumes

In this section we examine the question of the impact of AirBnB on the transaction volume in the context of Amsterdam. While the model presented in section 2 does not predict any change in sales volumes, if the market is inefficient, a demand shock may lead to an increase in sales volumes and a shorter time on the market if it takes time for buyers and sellers to coordinate on the equilibrium price.

As shown in table 6, when we instrument density with our shift-share instrument and include either the required controls for time and zip codes or our lasso-selected controls, we do not identify any significant effects of AirBnB density on transation volume. Ultimately we find that an increase of 100 in the average density of AirBnBs in the postcode is associated with a not economically meaningful increase in transaction volume of only 0.09 transactions.

5.2. Asking prices, sales prices and time on the market

5.2.1. Method

In this section, we explore the effect of AirBnB density on asking prices and time on the market, as well as its effect on the relationship between asking price, time on the the market and the final transaction price. Identifying this relationship is

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

methodologically challenging due to the underlying endogeneity of asking prices and time on the market. This problem arises as each of the asking price, sales price and time on the market depend on the motivation of both the seller and the buyer. Hence, using any one of these variables to predict another induces an endogeneity problem as the unobserved motivation of both the seller and the buyer is hidden in the error term.

To counteract the endogeneity issue, we exploit the fact that asking price is set by the seller before time on market or sales price are realised. We propose an instrumental variable approach based on the method suggested in Dubé and Legros (2016). We instrument the asking price of a property with the mean log sales price of all properties transacted before that property entered the market. These prior sales prices are residualised net of our lasso-selected controls. Using this instrument, we exploit the fact that the intertemporal relationships in the variables are unidirectional, meaning that the previous transactions are exogenous to the individual seller at the time of listing the asking price. This approach allows us to explore the effect of asking prices on final transaction prices and time on the market. The key assumption here are a strong first stage and the exclusion restriction. While we are able to test for the presence of a strong first stage, it is more difficult to test the exclusion restriction. In our case, this requires that previous asking prices affect contemporaneous time on market and sales price only via contemporaneous sales price. The greatest threat to our identification strategy is that previous sales prices in a postcode affect contemporaneous sales prices via expectations that are not captured by contemporaneous asking prices. As the model presented in section 2 proposes that higher sales price expectations will be capitalised by higher asking prices, and as this is corroborated by our results in section 5.2.1, we believe that there are no other remaining avenues through which previous asking prices affect our outcomes.

From this relationship, it becomes evident that we cannot instrument time on the market with time on the market in previous transactions. As contemporaneous asking price affects contemporaneous time on the market, it is likely that past asking prices affect past time on market, thus violating the exclusion restriction for a time on market instrument.

In a next step, we will combine this instrumental approach with the shift-share instrument for AirBnB density constructed in section 4.3.1 to explore how AirBnB listings and asking prices affect other outcomes simultaneously. Doing so, we will first explore the effect of AirBnB density on asking prices and time on the market. Next, we will introduce the instrumented asking prices to the model to identify the simultaneous effects of AirBnB density and asking prices on time on market and sales prices.

5.2.2. Results

We present results for these analyses in table 7. The first stage of our instrument for asking prices is negative and significant with an F-statistic of 324. We find that AirBnB density has a positive and significant effect on the asking price (column 1), and the size of this effect is very similar in magnitude to the effect of AirBnB density on the sales price found above (replicated for convenience in column 5). In both cases, the effect of an increase of 100 AirBnBs within a radius of 250 meters of a property, instrumented using our plausibly exogenous shift-share instrument, on house prices is of approximately 8 percent. this implies that the effects on sales prices identified in section 4 are driven by the capitalisation of higher expectations in higher asking prices.

Looking to time on the market, we do not find any significant or economically meaningful effects of either AirBnB density or asking prices on time on the market (in days)[4].

Finally, in examining final sales prices once more. we find significant and positive effects of asking prices on final sales prices. When asking price is included alone in the model as a predictor of sales price, we fine that a 1% increase in asking prices leads to a 0.6% increase in sales price. When including AirBnB density in the model, this effect remains similar in magnitude. When including both AirBnB density and asking price in the model, the effect of AirBnB density is reduced by half but remains significant. This suggests that AirBnB density and asking price are correlated, which is to be expected if AirBnBs locate in areas that are more sought-after. Assuming that areas sought after by locals are also those more attractive to tourists, this is consistent with our results presented in section 4.3.2.

6. Conclusion and Discussion

The question of how the sharing economy affects all of our lives has grown enormously in recent years. At the forefront of this discussion has been the effect of AirBnB and other home-sharing platforms on housing markets in large cities. 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. 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 asking and sale prices, with time on the market remaining unaffected. In an efficient market with inelastic supply, this effect will leave the transaction volume virtually unaffected. 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. Moreover, identifying the mechanisms underlying the house sale process transaction is challenging due to endogeneity and simultaneity.

[4]Note that since we have logged the asking price, the actual size of the effects of asking price presented in columns 3 and 4 are considerably smaller than the coefficients displayed (for instance, in column 3, a 1% increase in the asking price is associated with a $97.678 * \ln(1.01) = 0.97$ day increase in time on the market)

We identify the causal effect of AirBnB on residential property sales prices in three ways. First, we use 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. This allows us to account for any time-invariant property characteristics. Finally, 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. This allows us to overcome the issue of selection in the location of AirBnB listings. In a broader market equilibrium analysis, we overcome the endogeneity problem of asking price, sales price and time on the market by instrumenting the log asking price with the mean log sales price of all homes sold in the local post code area before the specific property entered the market.

In our empirical analysis, we first examine the reduced form effect of AirBnB listings on final sales prices. Across all model specifications, we find positive and significant effects of AirBnB density on sales prices in Amsterdam, confirming the predictions of our theoretical model. We find that the effect sizes are of similar magnitude across all specifications, which confirms the robustness of our results. Furthermore, we find larger effects of AirBnB proliferation on prices for homes with more rooms, but a relatively constant effect of AirBnB proliferation on sales prices over time. In our market equilibrium analysis we find that AirBnB listings and asking prices affect sale prices simultaneously, with time on the market and transaction volume unaffected. These results confirm our theoretical predictions and imply that the housing market in Amsterdam is efficient. The overall welfare effects of AirBnB listings are however ambiguous, and warrant further investigation. As presented in fig. 2, the growth in house prices began to exceed total growth (measured by the Consumer Price Index) in recent years. This implies that increasing house prices potentially increased overall inequalities.

With regard to policy implications, the effects we identify imply an economically significant effect of AirBnB density on house prices. We identify that an increase of 100 AirBnB listings within 250 metres of a property lead to an increase in prices between €15,052 and €36,125 at the mean price. The consequences of AirBnB on the Amsterdam housing market have been a top public and political priority in recent years. This has led to the implementation of a wide range of regulations, for example the City of Amsterdam reduced the maximum number of nights a host can rent out their entire property from 60 to 30 nights per year in January 2019. AirBnB was moreover banned in three neighbourhoods in the city in 2020. Our results indicate that the effect of AirBnB on house prices is substantial, however our broader market equilibrium analysis also shows that the housing market in Amsterdam is efficient. Hence, future policies need to be designed in a way to balance the potential redistributive effects of AirBnB. This could involve regulating AirBnB activities in the city centre to countervail the displacement of residents, without negatively affecting the efficiency of the housing market. Any policies adopted will need to address the overall welfare effects of AirBnB, including the life satisfaction of residents.

The present analysis could be extended in several ways. First, additional information on AirBnB guests and hosts could be included. This would allow us to, for instance, investigate changes in the composition of AirBnB listings following the implementation of both AirBnB and Amsterdam City policy changes in 2014, 2016 and 2019. This study could additionally be enriched by detailed socio-economic characteristics of buyers and sellers in the Amsterdam housing market, as well as additional information on the characteristics of local areas. For instance, if personal income of the sellers and buyers was available, we could examine the redistributive income effects of AirBnB between tenants and house owners. Furthermore, further research on the effects of recent regulations could provide guidance for future policy implementations.

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7. Tables and Figures

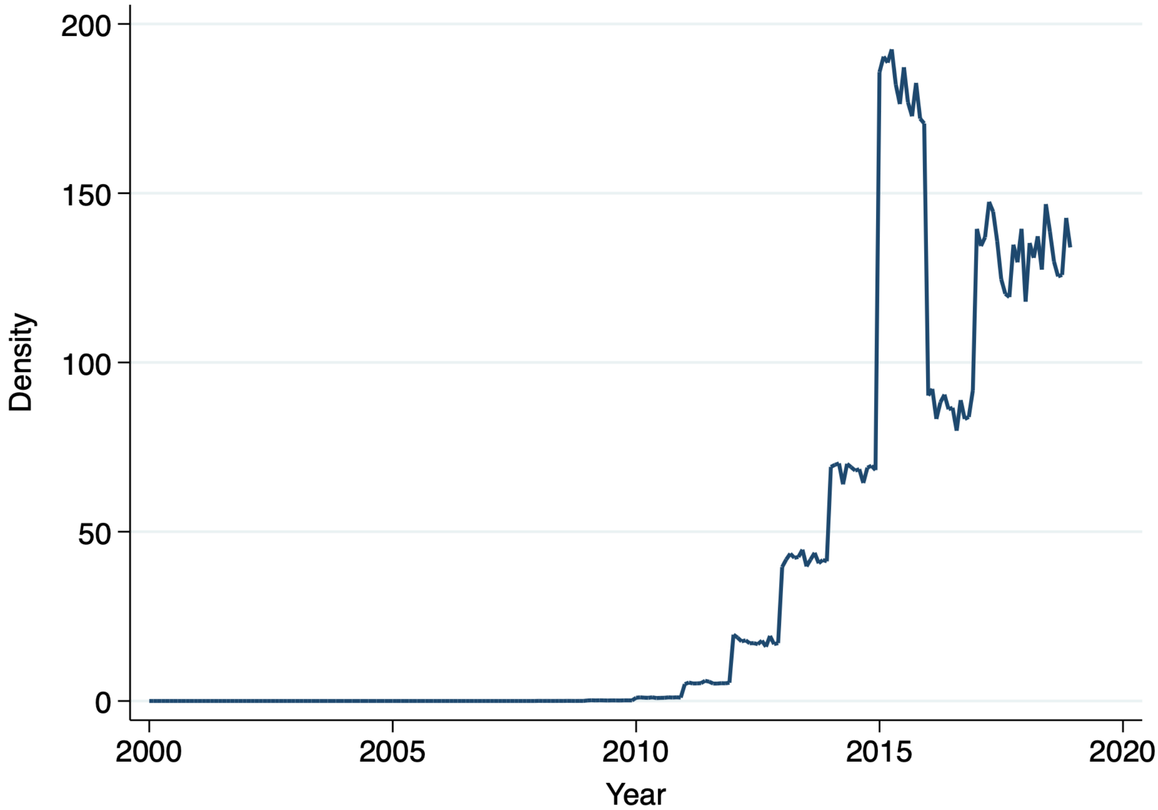

Figure 1: Airbnb growth in Amsterdam.
Notes: This graph plots the average number of AirBnB listings within 250m from 2000 to 2018 in Amsterdam per month.

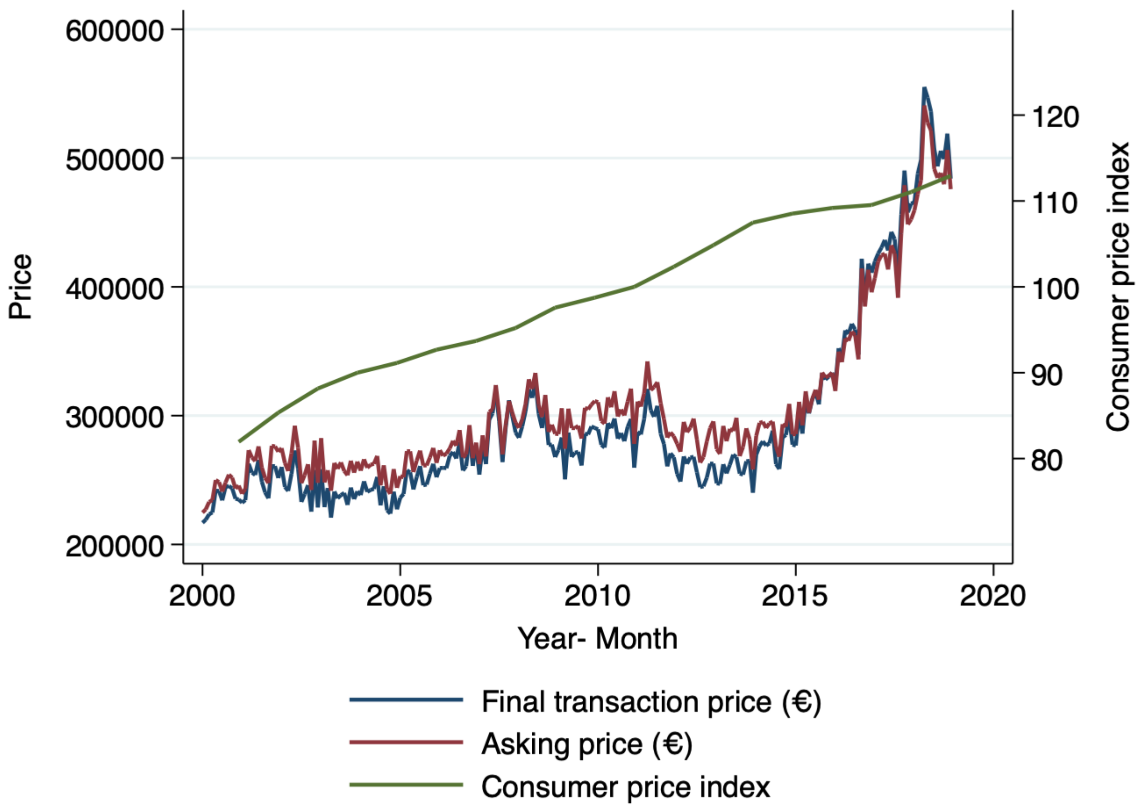

Figure 2: House price.

Notes: This graph plots the average transaction and asking price from 2000 to 2018 in Amsterdam per month. Further, we include the Consumer price index (2010 = 100) for the Netherlands. Data was taken from the World Development Indicators online database.

Table 1: Descriptive statistics.

	Count	Mean	Sd.	Min.	Max.
Final transaction price (€)	108441	301044.3	228107.8	50000.000	2500000
Asking price (€)	108390	310463.7	236209.7	25000.000	2500000
Time on market in days	108441	117.1642	183.045	0.000	3822.000
Garden present	108441	0.2731716	0.446	0.000	1.000
Parking available	108441	0.103992	0.305	0.000	1.000
Status as a monument	108441	0.0311506	0.174	0.000	1.000
Buyers cost or free	108441	1.036213	0.187	1.000	2.000
Size in m^2	108441	86.66707	42.957	25.000	1185.000
Volume in m^3	108088	242.5577	126.937	55.000	1000.000
number of rooms	108437	3.245903	1.331	0.000	16.000
Apartment	108441	0.8640182	0.343	0.000	1.000
Row house	108441	0.0914322	0.288	0.000	1.000
Semi-detached	108441	0.0028956	0.054	0.000	1.000
Corner house	108441	0.0254885	0.158	0.000	1.000
Two under one roof	108441	0.0080597	0.089	0.000	1.000
Detached house	108441	0.0081058	0.090	0.000	1.000
1500-1905	108441	0.1509946	0.358	0.000	1.000
1906-1930	108441	0.2794423	0.449	0.000	1.000
1931-1944	108441	0.0906115	0.287	0.000	1.000
1945-1959	108441	0.0496491	0.217	0.000	1.000
1960-1970	108441	0.0986896	0.298	0.000	1.000
1971-1980	108441	0.0400771	0.196	0.000	1.000
1981-1990	108441	0.1065188	0.309	0.000	1.000
1991-2000	108441	0.1207938	0.326	0.000	1.000
>=2001	108441	0.0632233	0.243	0.000	1.000
General state of quality of the house, score	108441	14.39498	1.766	2.000	18.000
Number of AirBnB listings within 250m	108441	0.4400001	0.906	0.000	6.850
Distance to nearest AirBnB listing	108441	274.7176	882.637	0.000	8842.936

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)			
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) 2008-2014	(2) 2015-2016	(3) 2017-2018	(4) $\leq$ 3 Rooms	(5) $\geq$ 4 Rooms
AirBnB density	0.234***	2.297	0.245*	0.058***	0.104***
	(0.043)	(6.236)	(0.132)	(0.014)	(0.013)
Mean Price	267,043	342,091	472,541	240,543	425,246
N	79,355	17,092	11,637	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.

Table 6: Transaction Volumes

	(1) 1st Stage	(2) Reduced Form	(3) IV	(4) IV	(5) IV + controls
Dep. Var.	Density	Transactions			
Instrument	0.554***	0.957***			
	(0.090)	(0.313)			
AirBnB density			1.727***	0.121	0.091
			(0.332)	(0.284)	(0.287)
Controls	None	None	None	Month, Zip Code	Post-Lasso
N	14,111	14,111	14,111	14,111	14,104

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

Table 7: Asking Price, Time on Market and Sales Price

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	Ln(Asking Price)	Time on Market			ln(Sales Price)		
AirBnB density	0.081***	–4.310		–13.694	0.077***		0.030***
	(0.012)	(3.953)		(45.403)	(0.013)		(0.008)
ln(Asking Price)			97.678	115.836		0.623***	0.583***
			(506.283)	(565.356)		(0.096)	(0.100)
Controls	Post-Lasso	Post-Lasso	Post-Lasso, Month, Zip Code	Post-Lasso, Month, Zip Code	Post-Lasso	Post-Lasso, Month, Zip Code	Post-Lasso, Month, Zip Code
N	108,063	108,084	106,051	106,051	108,084	106,051	106,051

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)
multiple_sales	
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 (^{2})	–0.005***
	(0.000)
Volume (^{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. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.