Airbnb Impact on the Housing Market: Evidence from Amsterdam

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Abstract

We explored the effect of Airbnb listings exponential increase on the price of real estate in Amsterdam. Using data from *Brainbay* we estimated several models (hedonic regression with fixed effects, instrumental regression and spatial autoregressive model). We got significantly positive result of Airbnb expanse on prices in all models with coefficients varying from $0,02\%$ up to $0,1\%$. Additionally we estimated the effect of Airbnb on the other parameters of the housing market. Using spatially lagged survival analysis with IV we showed that causal effect of Airbnb on time-on-market is negative. We discuss possible mechanisms and policy implications.

Contents

1 Introduction

The sharing economy stands for a set of peer-to-peer marketplaces where small suppliers (mostly individuals) can find consumers. This economy has grown dramatically in the XXI century. The growth is mainly due to technological innovations that allow effective matching between the supplier of the product or service and the consumer. The example of such products is Uber, Airbnb, and many other products.

In this paper we want to analyze the influence of the home sharing platform Airbnb on the real estate market in the Netherlands. Airbnb was founded in 2008 and experienced rapid growth. Economic theory predicts that home sharing platforms improve the efficiency of the real estate market since it reduces the cost of finding renters and allows to easily rent out excess rooms. Airbnb helps to find customers faster.

Additionally, it allows generating additional profits in case of excess or temporarily free rooms. It means that houses can generate higher revenues, thus, real estate generates higher returns, consequently, prices on real estate should increase. However, it is only a first glimpse and we will analyze all mechanisms.

Moreover, short-term rentals might become more profitable than long-term rentals. It results in reallocation from one market to another. Thus, we expect that prices on the short-term market should go down, while prices for a long-term rent should increase. This increases the price of the houses.

On Figure 1 we can see that that the total number of tourists in Amsterdam increased substantially over the period 2009-2019 (a 43% increase). At the same time, the total number of tourists in Europe increased by 63% [1]. It is about 5% every year. Over the period 2000 - 2007, there was only a 3% growth. Of course, we cannot attribute this fact to the foundation of Airbnb, but we want to emphasize that the tourism industry was growing very fast after 2008. Additionally, it is important to mention that Amsterdam suffers from overtourism according to tourists officials[2]. We mention this fact because this increase pushes the rental prices up in attractive for tourism districts. Moreover, this growth is volatile and the foundation of Airbnb coincides with rapid growth in the tourism industry.

There are several reasons, why Airbnb might have no effect on the rental price. First, the market of short-term rentals might be too small compared to long-term rentals. Additionally, a separation between short-term and long-term markets might be too rigid, and there will not be any reallocation (Barron et al. (2021)).

We also have to mention externalities here. Tourists are the main side of the demand in the short-term rentals market. Thus, increased supply probably resulted in demand value increase. We have already mentioned overtourism in Amsterdam when streets are overcrowded, too noisy, the mass of people are also responsible for significant many physical impacts (destruction of nature) and congestion. This is a negative externality to all citizens. At the same time, there is also a positive externality for business, since the mass of tourists increases the demand for goods and services. We want to summarize the effects of Airbnb's foundation on the market with a diagram from Sheppard and Udell (2016).

[1] United Nations World Tourism Organization (UNWTO)
[2] How Amsterdam is fighting back against mass tourism

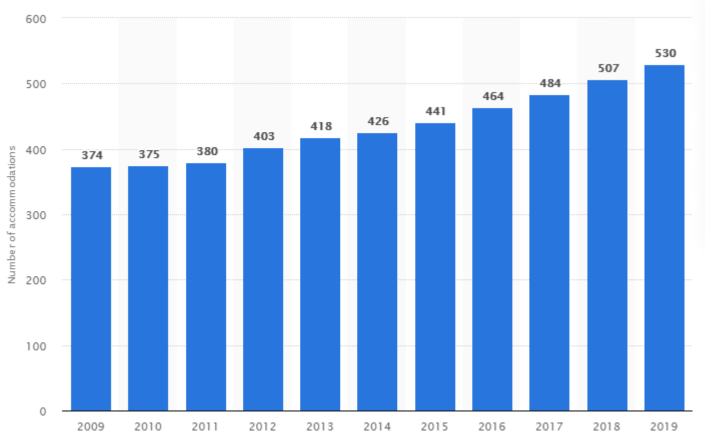

Figure 1: Total number of tourist accommodations in Amsterdam

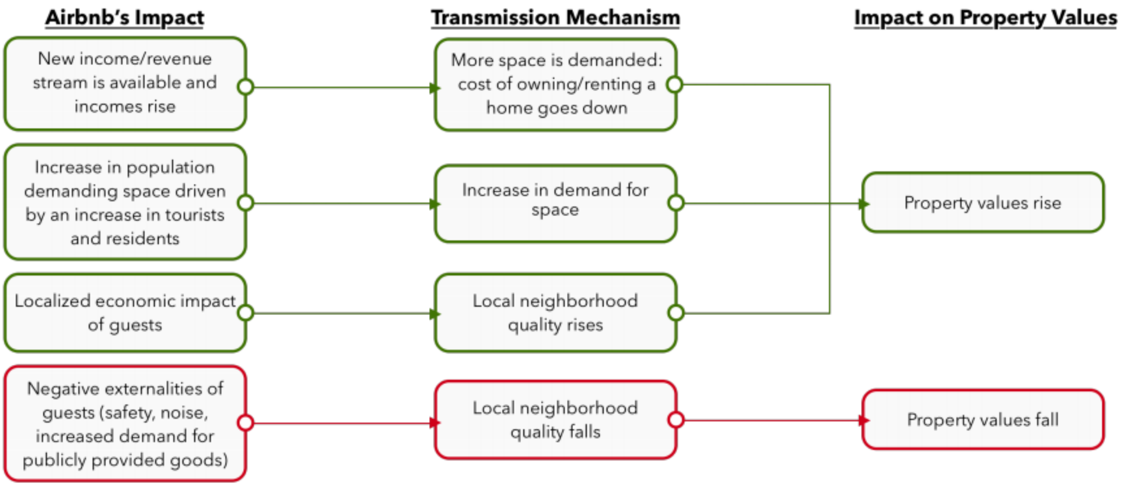

Figure 2: Diagram from Sheppard and Udell (2016)

1.1 Mechanism of house prices formation

Here we will further describe the model, how Airbnb expansion can affect the house prices. In Tab. 1 we present the "naive" list of possible determinants of house prices that can affect house prices. During our research, we mainly try to find identification strategy that allows us to capture causal effects of Airbnb without controlling for this determinants. Now let us move to the effect of Airbnb.

Assume housing supply is fixed in the short-run. The population is divided into house owners (supply) and rent-seekers (demand). Supply is coming from two sources: long-term rent seekers (we can consider ownership as a form of long-term rent) and short-term rent seekers. So, two different rents are determined in equilibrium. Note that long-term rent can't be higher than short-term. Indeed, the profit of an owner is determined as

$$\pi = \text{Time of house being rent} \times \text{Rent}$$

In equilibrium the profit from long-term rent is equal to the profit from short-term rent. Additional assumption is that some time is required to find a new tenant.

Table 1: Possible additional determinants

House Price	
Local	Global
Pollution	Income level
Noise	Risk-free rate r
Air	Unemployment level
Neighbors	Inflation
Distance to job	Migration
Crime rate	Liquidity constraints
Infrastructure	

Airbnb increases the quality of matching between short-time rent seekers and owners. Hence for the short-term rent "time of house being rented" increases. For market to stay balanced owners switch to short-term rent. So, the short-term rent price decreases, long-term rent price increases (though staying lower than short-term rent prices), income of house owner increases. We should observe the following effects:

1. Hotel prices decrease: hotel prices are the most observable example of short-term rent prices.

2. Fundamental prices of houses increases (fundamental price is the discounted sum of future profits from house):

$$p = \sum_{t=0}^{\infty} \frac{\mathbb{E}Rent_t}{(1+r)^t}$$

3. Even if we assume price bubbles on housing market, such shock is unexpected, so it should lead to the increase in market price of house.

4. The effect of the shock should be greater for the houses that are more suitable for the short-term rent.

5. If supply is not fixed in long-term (which may be possible in historical cities) then we will see increase in construction.

Overall, this informal model gives us testable short-term predictions that we can explore using given data.

1.2 Time-on-market and asking price: economic meaning

Note that in real life housing market is a market with an imperfect information. So, neither owner nor rent-seekers do not observe the market itself. Moreover, different rent-seekers have different preferences on houses. The matching process takes some time and adds imperfections. Therefore, to model this market more thoroughly we have to implement some kind of combination between search model and bargaining model. The example of timing from article by Dubé and Legros (2016) is presented on Figure 3.

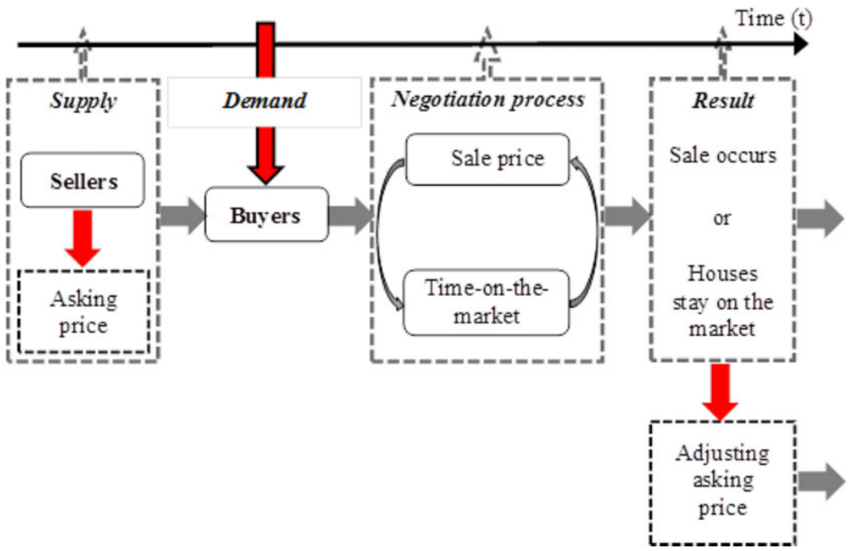

Figure 3: Diagram from Dubé and Legros (2016)

The asking price in this model reflects general expectations of seller about the price of house. As we can see on Figure 10 this price may be lower or higher than the final price, so it is not reserve price or minimal price. In the simplest model, with each new potential buyer seller either sell the house or update his beliefs. If his beliefs were too pessimistic (buyer is ready to pay the price), the process is finished. If his beliefs were too optimistic, they reestimate their beliefs. Than longer time-on-market should be associated with beliefs that are farther from buyer's beliefs.

So, generally, we may expect longer time-on-market for more "rare" in terms of market characteristics houses. This goes in line with articles such as Dubé and Legros (2016); Campbell et al. (2011); Cheng et al. (2008).

What will be the impact of Airbnb? Firstly, Airbnb increases the prices of houses and hence reduces the time-on-market. Secondly, Airbnb makes houses more liquid: it is easier to get immediate profits from renting the house, so matching process will become more rapid.

But it is not obvious: the effect may be opposite. Airbnb makes it easier to get profits from the market, so the seller have a greater opportunity cost (they are more patient). This is prediction we are going to test in our article.

2 Literature review

The influence of Airbnb was explored in several papers. Barron et al. (2021) used data on US Airbnb listing and house prices utilizing non-spatial panel regressions. They found that the prices of houses increased due to reallocation from long-term rental to short-term rentals. Rental prices increased as well. To fight endogeneity of the number of Airbnb listing the authors used Google Trend Index regarding "Aribnb"search query around the world. It is exogenous to the local market of Amsterdam and certainly correlate with popularity of Airbnb. However, there was a trend in the popularity that might lead to spurious correlation. In out paper we additionally divide the popularity index on the number of tourists in Europe.

Sheppard and Udell (2016) that in New York City Airbnb availability increased the house price significantly. The authors used diff-in-diff approach suggesting that properties that are subject to the Airbnb treatment increase in value by about 31%.

3 Data Description

We use the data provided by *Brainbay*. This data covers sufficient amount (108, 441) of transactions between 2008 and 2018. It includes set of house characteristics, categorical information on the period of construction and the type of the house for each transaction. Also for each transaction we have data on the number of Airbnb listings in 250 m radius (Density) and the distance to the closest Airbnb listing (Distance) in the year of sale. Regarding transaction itself, we have the final price of the transaction, the time on the market between the start of sales and the sale itself and the asking price.

We cleared the data from outliers by deleting higher 0, 05% of the observations for the variables Price, Asking price, their difference, Distance, Rooms and Size. Additionally we deleted the lowest 0, 05% for the difference of the prices.[3] We resulted in 105, 384 observations. We present summary statistics for non-categorical variables in Tab. 2.

Table 2: Summary statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Price	284,414.200	177,049.800	50,000	173,000	331,500	1,605,000
Asking Price	293,118.100	183,204.100	52,500	179,000	340,000	1,700,000
Price per meter	3,418.519	1,277.256	720.000	2,457.972	4,111.111	13,750.000
Asking price per meter	3,509.242	1,248.636	750	2,555.6	4,230.8	14,500
Change in price	8,703.854	25,359.690	−69,500	0	16,000	209,500
Time on market	108.700	148.426	0	22	131	1,197
Distance (to Airbnb)	241.473	732.143	0	0	76.3	6,259
Density (of Airbnb)	43.844	90.529	0	0	36	685
Garden	0.265	0.441	0	0	1	1
Size	83.717	35.161	25	60	100	298
Volume	236.474	116.449	55	160	277	3,653
Rooms	3.171	1.169	0	2	4	8
Parking	0.101	0.301	0	0	0	1
Monument	0.030	0.169	0	0	0	1
Quality	14.397	1.753	2	14	14	18

Quality is categorical and possible endogenous variable, but due to sufficient amount of possible values and monotonic nature we take it as given and assuming strictly depending on house characteristics.

First, we want to visualize. Airbnb is usually used by tourists, thus we except that the number of listing is concentrated most near the center[4] of Amsterdam. The Figure 4 demonstrates that this hypothesis is correct.

[3] Informally we do not expect too low negative and too high positive differences to bee due to some non-market asking prices expectations.

[4] We defined the center as 4-digit zip-codes: 1011, 1012, 1015-1019, 1052-1054, 1071-1074, 1091-1093. This specification is based on anecdotal evidence. We use it for illustrative purposes mainly.

That means that real estate prices in the city center and outside should be different. We observe this on Figure 7. There we present the average prices of the apartments in the city center and outside.

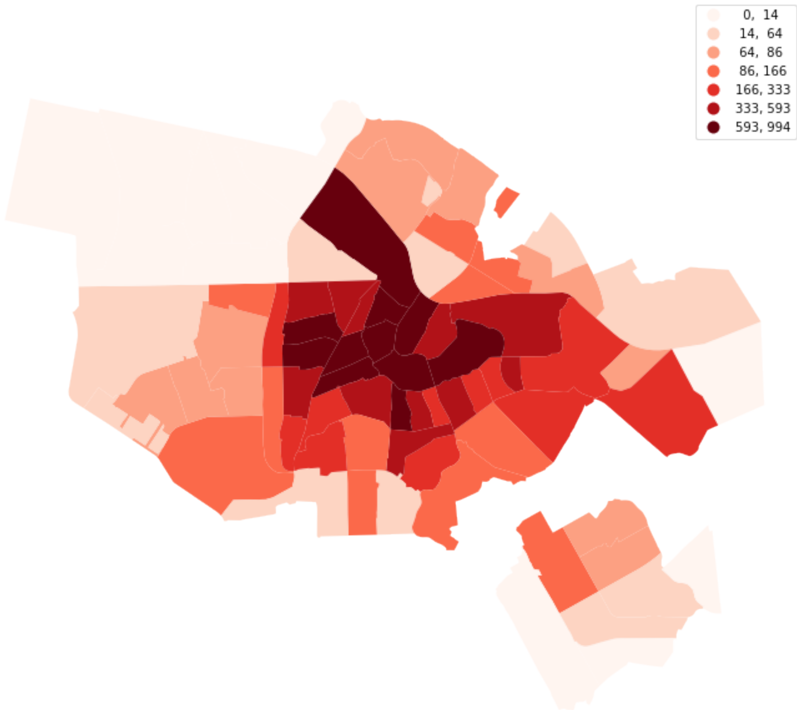

Figure 4: Number of listings in each 4-digit zip-code neighborhood (2015)

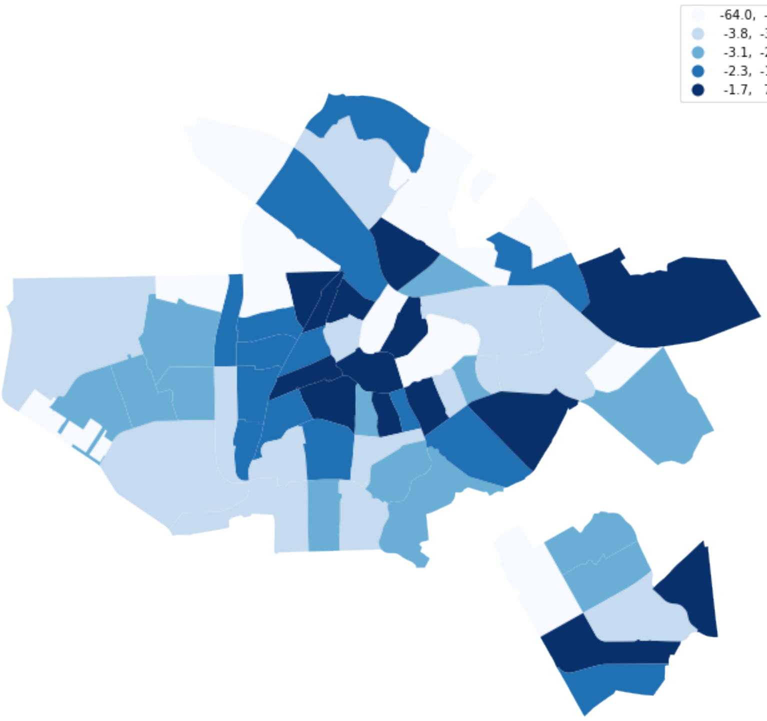

Figure 5: Change in apartments prices in 2000-2007

The Figure 10 shows for real estate sold in 2009-2019 the difference between asking price and real price. This graph is interesting because before 2016 the difference was positive, meaning that sellers were decreasing their prices. At the same time, after 2016 the difference was negative, it means that the actual price was higher then asking price. Probably, it is the result of positive growth of demand on real estate market and rapid growth of prices (see Figure 7).

4 Empirical Strategy

4.1 Hedonic regression (simple OLS)

As one of the basic models we use Hedonic regression, which takes roots from Rosen (1974). It is used for estimating prices for composite goods, such as buildings or apartments. It is based on an assumption that the price of the composite good

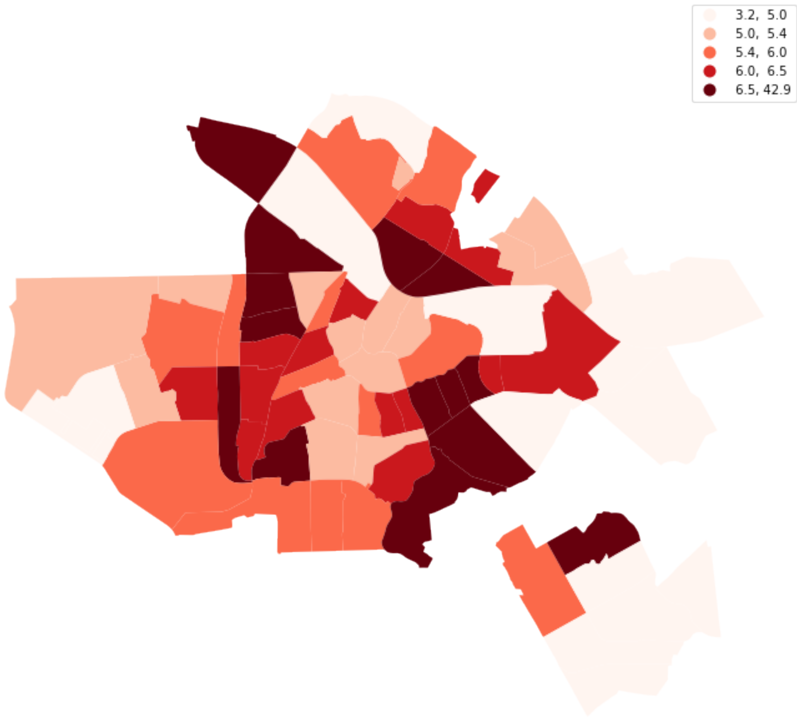

Figure 6: Change in apartments prices in 2010-2018

depends on a certain set of characteristics. For the apartment, it may be

$$P_a = f(X, Y, Z)$$

where X is some apartment-specific characteristics vector, Y are some neighborhood-specific characteristics and Z are more general characteristics (city characteristics, for example). The number of explanatory variables can be changed. It usually results in the following empirical model

$$P_{a,n,c} = \beta X_{a,n,c} + \alpha_{n,c} + \gamma_c + \epsilon_{a,n,c}$$

Here $P_{a,n,c}$ is a price of an apartment a in neighborhood n of city c, $X_{a,n,c}$ are apartment-specific characteristics, $\alpha_{n,c}$ is neighborhood fixed effect and γ_c is city fixed effect (note that one neighborhood fixed effect has to be omitted if city fixed effect is present). Depending on the characteristics of data, we can omit or add some fixed effects, or include time fixed effects or time trends. Specifically for our case, we choose the following specification

$$\ln p_{a,n,t} = \gamma Airbnb_{a,n,c} + \beta X_{a,n,c} + \alpha_{n,t} + \epsilon_{a,n,t}$$

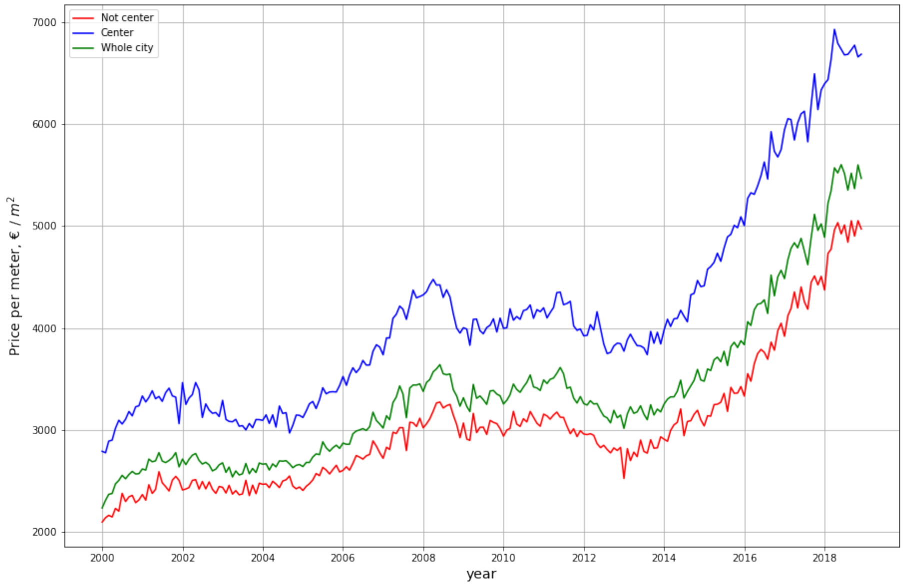

Figure 7: Prices on apartments in the center and outside of the center

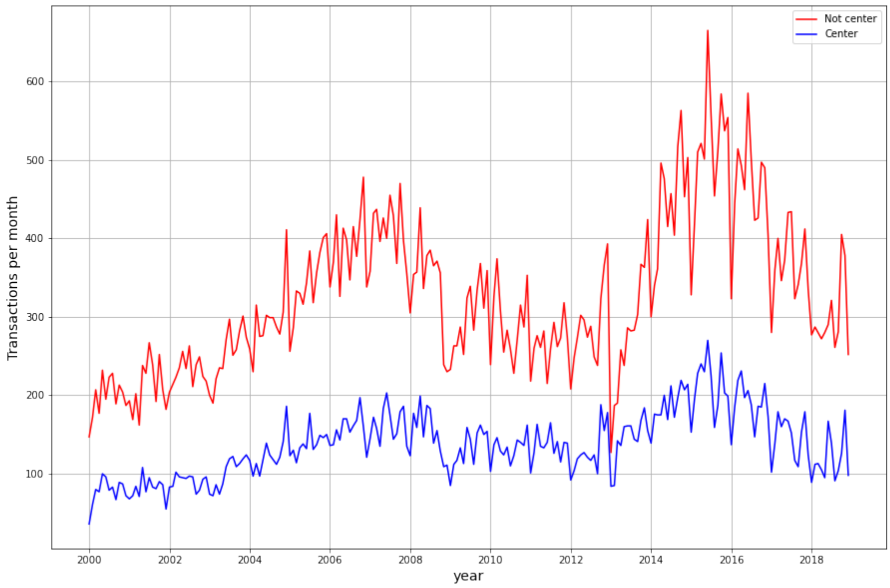

Figure 8: Number of transactions for the period 2009-2018

Here $p_{a,n,t}$ is a realized apartment price per squared meters (we choose this measure here as it is easier to interpret). $Airbnb_{a,n,c}$ is a vector of different measures for exposure to Airbnb (we explore mainly given variables such as Density – the number of Airbnb listings in 250 meters radius and Distance to the closest Airbnb

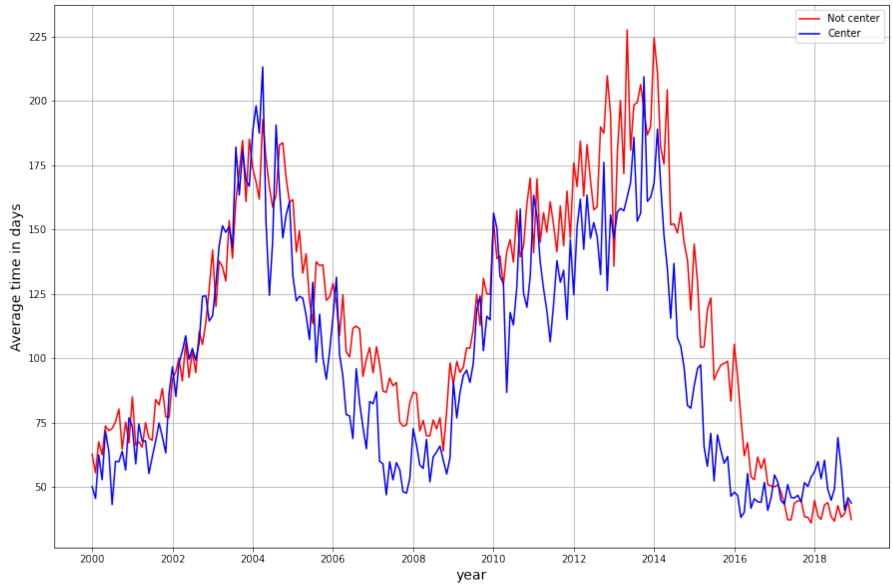

Figure 9: Average time on market for sold property

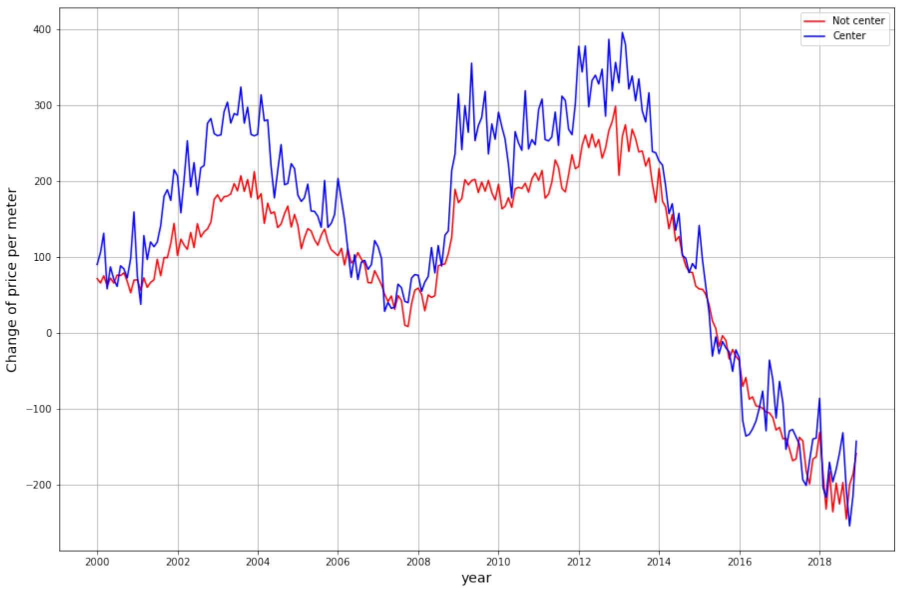

Figure 10: Change of the price (asking price minus price of sale)

listing). $X_{a,n,c}$ is a set of house characteristics and $\alpha_{n,t}$ are rime-location fixed effects. We cluster errors at location level following Dröes and Koster (2016). Note, this specification depends on specific identification. More precisely all unobserved effects should be captured by location-time fixed effects.

4.2 Fixed effect model with Bartik(1991) instrument

We follow Barron et al. (2021) and utilize Google Trends regarding "Airbnb" and the number of tourist spots (zoo, museums, galleries, bars, and art centers). The number of these attractions is counted within a range of 600 meters. Then we divide the popularity of the query "Airbnb" on the number of tourists in Europe that is also exogenous. We do this to remove the trend due to an increase in the popularity of tourism. We used the interacting Bartik instrument (Bartik (1991)) that is an interaction of a plausibly exogenous time series (Google trends) with a potentially endogenous cross-sectional exposure variable (number of tourist spots). We checked the relevance of our instrument then. It is correlated with the density of Airbnb listings near each of the observations. We use TSLS IV regression for the estimation. The results can be found in the next section. We use only transactions over the period 2009-2018.

To estimate the nonlinear effect of Airbnb listing we include the square of the number of Airbnb listing near each apartment in the sample. We used the square of our Bartik instrument.

To estimate interaction terms with the type of houses. We utilize the same strategy. We used interaction terms with our Bartik instrument for IV regression with fixed effect.

4.3 Spatial Autoregressive Model (SAR)

In this class of models we take into account the fact that dependent variables have a spatial impact on each other. To see that it takes place we made a regression of spatial regression residuals on their spatial lags. On Figure 11 we can see that, indeed, there is a spatial dependence.

Formal equation for the SAR model is the following:

$$y = \rho W y + \beta X + \mu + \epsilon$$

Here W is the spatial weights matrix and μ is a fixed effects vector.
The variable of interest was an average log of property price in each district (pc4). The weighting matrix is constructed for contiguous spatial units so that it is 1 for units that have shared borders.

4.4 Survival Analysis

All information we have is on completed sales. However, we do not observe the apartments which were exhibited for sale before 2018, but were not sold in 2018. To eliminate selection bias we divide out data into 2 parts: last year (2018) and the 2009-2017. Figure 9 shows that the maximal time on market indicator was about 200 days. Additionally, it decreased significantly in 2018. Thus, we can assume that most of houses that were exhibited in 2017 were sold in 2018. We have censored data and use survival analyses to estimate the influence of Airbnb and other factor on probability to be sold. Additionally, this helps to estimate the factors that influence

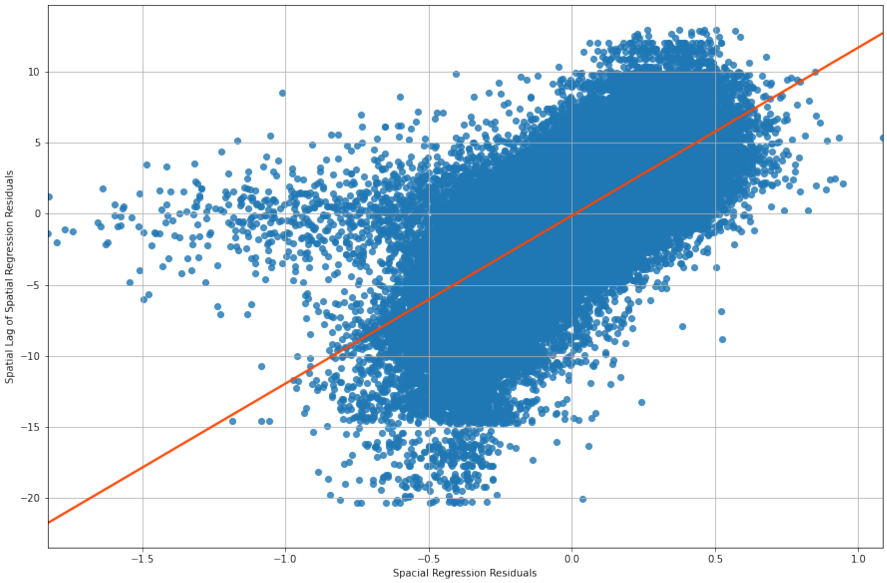

Figure 11: Regression plot of spatial residuals on their spatial lags

time on market. We consider time period 2009-2018. We consider the last year. In 2018 there were 5004 transactions. There are 480 right-censored spells.

4.4.1 Simple Cox Model

We use Cox Proportional Survival Analyses (Cox (1972)) to model probability of being sold $h(t)$ in period t. Here period t means that the house has been on market for t periods.

$$h(t) = h_0(t) \times \exp(b_1x_1 + b_2x_2 + ... + b_px_p) \tag{1}$$

In the simple model we include only controls and *Density*. Additionally, we include fixed effects on time and space (zip-codes).

4.4.2 Cox Model with IV Estimation

We want to fight endogeneity of *Density* with Bartik instrument that we used in previous models. Here we use simple TSLS model. First, we regress *Density* on our instrument and controls. Then we take predictions and plug them into our Survival Model. In the next section you can find the results of our regressions.

Unfortunately, linear 2SLS is biased and not efficient if we use non-linear estimation on the second stage (and Cox Proportional Model is non-linear). However, IV estimation fow survival models are not developed, and we use linear 2SLS that is still consistent(MacKenzie (2014), Cheng et al. (2008)).

4.4.3 Cox Model with IV Estimation and Spatial Autocorrelations

As we mentioned in Subsection 7 there is spatial dependence in the dataset (see also Tobler's first law of geography: "everything is related to everything else, but near things are more related than distant things"). To model this spatial dependence we decided to divide Amsterdam area into small rectangles, overall into $10 \times 10 = 100$ rectangles, numbering them from 0 to 99 (see the example of such division in Figure 12). After that the weight matrix with size 100×100 is constructed: the i'th row represents a vector with ones and zeros where indices of ones are numbers of rectangles which are neighbors for i'th rectangle. We constructed these rectangles since a weight matrix with size 100000×100000 simply cannot locate in the memory of our computers. Then we calculate the average log of price per m^2 within each small rectangle. And finally, we add 100 new regressors to the regressor matrix, where i'th new regressor is 0 if i'th rectangle is not a neighbor for the current rectangle (where thurren observation is located), and the average log price per m^2 in the i'th rectangle otherwise. We used Rook's case for adjacency matrix.

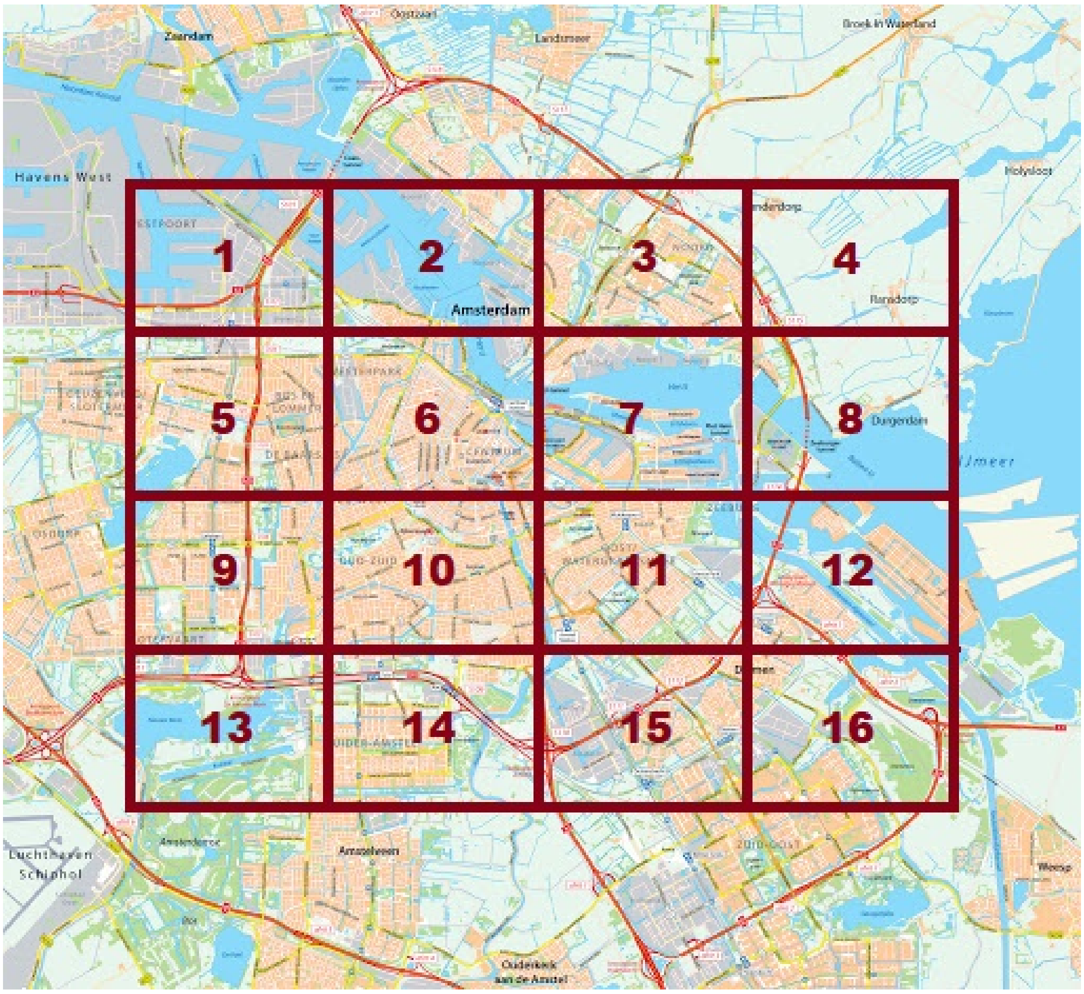

Figure 12: Example of area division into rectangles

We develop Spatial Lagged Model to use it for control on neighbors. We include logarithm of mean prices in the neighboring triangular to each observation. Of course, it would be better to have adjacency matrix N×N, but it is to computationally consuming. We assume that our approximation can help at least partially fight spatial correlation. Thus, our model is:

$$h(t) = h_0(t) \times \exp(X\beta + P\gamma) \tag{2}$$

where P is a matrix of prices of neighbors in the same period.

5 Results

5.1 "Naive" hedonic estimation

We present result of "naive" estimation described in subsection 4.1 in the tab. 3. As we can see the coefficient is pretty stable. Specifications (2)-(7) explore explanatory variables in different combinations include house characteristics, fixed effects on the period of construction, type of the house, and other house controls.

Table 3: "Naive" hedonistic estimation: all years

Dependent Variable:	ln of Price per meters						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Density	0.0019***	0.0010***	0.0015***	0.0015***	0.0015***		
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)		
Distance		-8×10^{-5} ***	2.61×10^{-6}	2.61×10^{-6}		-1.83×10^{-5} ***	
		(8.41×10^{-6})	(6.9×10^{-6})	(6.9×10^{-6})		(5.64×10^{-6})	
Airbnb in < 250 m							0.2541***
(dummy)							(0.0083)
ln Volume		-0.0328	-0.0164	-0.0164	-0.0167	-0.0296	-0.0065
		(0.0298)	(0.0300)	(0.0300)	(0.0300)	(0.0267)	(0.0262)
Garden		0.0545***	0.0457***	0.0457***	0.0457***	0.0413***	0.0444***
		(0.0070)	(0.0076)	(0.0076)	(0.0076)	(0.0080)	(0.0069)
Rooms		-0.0016	0.0039	0.0039	0.0040	0.0055	-0.0064
		(0.0042)	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0042)
Parking		0.0382	0.0392	0.0392	0.0391	0.0246	0.0366
		(0.0244)	(0.0245)	(0.0245)	(0.0244)	(0.0255)	(0.0271)
Quality		0.0308***	0.0250***	0.0250***	0.0250***	0.0217***	0.0268***
		(0.0017)	(0.0021)	(0.0021)	(0.0022)	(0.0023)	(0.0021)
Monument		0.1233***	0.1476***	0.1476***	0.1475***	0.1553***	0.1285***
		(0.0206)	(0.0203)	(0.0203)	(0.0203)	(0.0197)	(0.0199)
Fixed-effects							
Year	Yes	Yes					
4-digit zip-code & Month			Yes				
6-digit zip-code & Month				Yes	Yes	Yes	Yes
Period of construction				Yes	Yes	Yes	Yes
Type of the house				Yes	Yes	Yes	Yes
Fit statistics							
Observations	105,384	105,384	105,384	105,384	105,384	105,384	105,384
R^2	0.38044	0.62203	0.45895	0.45895	0.45892	0.32528	0.44199
Within R^2	0.16093	0.48812	0.45895	0.45895	0.45892	0.32528	0.44199

Errors are clustered at 4-digit zip-code level
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

In tab. 4 we repeat the same estimations for the years after Airbnb started it's expansion (2008). The results are close to previous, so in the next estimations we will limit our analysis to years 2009-2018.

Table 4: "Naive" hedonistic estimation: 2009-2018

Dependent Variable:	ln of Price per meters						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Density	0.0019***	0.0010***	0.0011***	0.0011***	0.0012***		
	(0.0002)	(0.0001)	(9.45×10^{-5})	(9.45×10^{-5})	(9.91×10^{-5})		
Distance		-8.5×10^{-5} ***	-6.91×10^{-5} ***	-6.91×10^{-5} ***		-0.0001***	
		(1.19×10^{-5})	(7.66×10^{-6})	(7.66×10^{-6})		(1.17×10^{-5})	
Airbnb in < 250 my							0.1774***
(dummy)							(0.0088)
ln Volume		-0.0483	0.0345	0.0345	0.0383	0.0423	0.0402
		(0.0312)	(0.0305)	(0.0305)	(0.0309)	(0.0255)	(0.0258)
Garden		0.0532***	0.0435***	0.0435***	0.0426***	0.0390***	0.0399***
		(0.0078)	(0.0072)	(0.0072)	(0.0074)	(0.0074)	(0.0074)
Rooms		0.0058	-0.0085	-0.0085	-0.0089	-0.0172***	-0.0163***
		(0.0048)	(0.0053)	(0.0053)	(0.0054)	(0.0053)	(0.0053)
Parking		0.0227	0.0427*	0.0427*	0.0417	0.0280	0.0265
		(0.0248)	(0.0249)	(0.0249)	(0.0269)	(0.0266)	(0.0292)
Quality		0.0328***	0.0299***	0.0299***	0.0296***	0.0282***	0.0284***
		(0.0019)	(0.0021)	(0.0021)	(0.0021)	(0.0024)	(0.0024)
Monument		0.1178***	0.1296***	0.1296***	0.1327***	0.1204***	0.1199***
		(0.0211)	(0.0200)	(0.0200)	(0.0199)	(0.0198)	(0.0198)
Fixed-effects							
Year	Yes	Yes					
4-digit zip-code & Month			Yes				
6-digit zip-code & Month				Yes	Yes	Yes	Yes
Period of construction				Yes	Yes	Yes	Yes
Type of the house				Yes	Yes	Yes	Yes
Fit statistics							
Observations	60,362	60,362	60,362	60,362	60,362	60,362	60,362
R^2	0.38559	0.60766	0.47437	0.47437	0.46255	0.38308	0.38633
Within R^2	0.24585	0.51843	0.47437	0.47437	0.46255	0.38308	0.38633

Errors are clustered at 4-digit zip-code level
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

We can see that results are pretty stable: additional Airbnb apartments in 250 meters radius increase the price by $\sim 0.1\%$. Distance affects the price negatively, which supports our understanding that Airbnb positively affects real estate prices. The Airbnb dummy has the higher positive coefficient than density, that suggest non-linear effect (diminishing marginal returns of Airbnb in the neighborhood).

However high coefficient here may be the sign not only of the positive causation effect but also of some unobservable effect, that positively affects both dependent and explanatory variables. Such variable may be some "attractiveness" of the place. That's why we used IV estimators to re-estimate the casual effect and get rid of endogeneity.

Also, we decided to check for the non-linearity of the effect. Results of the same estimation are presented in Tab. 5. As we can see, the specifications with squared densities for all specifications (1, 2 and 6). Estimation with logarithmic explanatory variable (3 and 4) also result in significant estimates. We can definitely say that price exhibits diminishing returns from the number of Airbnb listings in 250 meters radius. Note that the first-order effect is significantly higher than in 4 and similar with coefficients for Airbnb dummy)$\sim 0.2 - 0.3\%$.

The specifications (5) and (6) estimates regressions with interactions for the type of houses. That shows that certain types of houses (row, semi-detached, and corner houses) got a more significant increase in price than others. That can be explained that Airbnb apartments are more often made in such types of houses, so demand on them will increase more and the price also (in SR assumption that supply is fixed).

Table 5: "Naive" hedonistic estimation: non-linear effects and interactions

Dependent Variable:			ln price_size			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Density	0.0030***	0.0030***			0.0012***	0.0027***
	(0.0002)	(0.0002)			(9.57×10^{-5})	(0.0002)
Density^2	-4.76×10^{-6} ***	-4.76×10^{-6} ***				-4.32×10^{-6} ***
	(6.12×10^{-7})	(6.12×10^{-7})				(5.76×10^{-7})
ln (Density +1)			0.0763***	0.0637***		
			(0.0036)	(0.0031)		
Type 1 × Density					0.0015***	0.0013***
(row house)					(0.0003)	(0.0002)
Type 2 × Density					0.0013***	0.0011***
(semi-detached)					(0.0004)	(0.0004)
Type 3 × Density					0.0013***	0.0011***
(corner house)					(0.0003)	(0.0003)
Type 4 × Density					0.0003	5.8×10^{-5}
(two under one roof)					(0.0005)	(0.0004)
Type 5 × Density					0.0008	4.05×10^{-5}
(detached house)					(0.0005)	(0.0005)
ln Volume	0.0301	0.0301	0.0257	0.0268	0.0374	0.0281
	(0.0323)	(0.0323)	(0.0294)	(0.0285)	(0.0308)	(0.0314)
Garden	0.0461***	0.0461***	0.0466***	0.0465***	0.0479***	0.0509***
	(0.0071)	(0.0071)	(0.0070)	(0.0069)	(0.0070)	(0.0068)
Rooms	-0.0079	-0.0079	-0.0094*	-0.0118**	-0.0101*	-0.0102**
	(0.0052)	(0.0052)	(0.0049)	(0.0048)	(0.0053)	(0.0049)
Parking	0.0449*	0.0449*	0.0332	0.0339	0.0421	0.0445*
	(0.0248)	(0.0248)	(0.0244)	(0.0263)	(0.0263)	(0.0252)
Quality	0.0296***	0.0296***	0.0298***	0.0299***	0.0296***	0.0297***
	(0.0020)	(0.0020)	(0.0021)	(0.0021)	(0.0021)	(0.0020)
Monument	0.1141***	0.1141***	0.1136***	0.1112***	0.1270***	0.1086***
	(0.0197)	(0.0197)	(0.0191)	(0.0201)	(0.0193)	(0.0198)
Fixed-effects						
Year	Yes		Yes			
4-digit zip-code & Month		Yes		Yes	Yes	Yes
Period of construction	Yes	Yes	Yes	Yes	Yes	Yes
Type of the house	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	60,362	60,362	60,362	66,295	60,362	66,295
R^2	0.50382	0.50382	0.49230	0.47408	0.46633	0.49729
Within R^2	0.50382	0.50382	0.49230	0.47408	0.46633	0.49729

Errors are clustered at 4-digit zip-code level
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

5.2 Fixed effect model with Bartik instrument

In Table 6 we can see the results of our 2SLS IV estimation. In regression (1) we test the relevance of our instrument. As can be seen, it is highly correlated with our target variable *Density* which is the number of Airbnb listings in the nearest 250m. In regression (2) we estimated our base IV regression. As can be seen, the coefficient *Density* is positive and significant. It means that Airbnb's popularity increases price in the district if we believe in the relevance and validity of our instrument. We can also see that compared to the naive regression in Table 3 the coefficient is twice smaller. We exclude endogeneity from our variable *Density* and diminish the effects of possible omitted variables.

Then we checked the non-linearity. Regression (3) demonstrates the estimation for non-linearity cases. Surprisingly, here we have a U-shaped curve and the apex of a parabola in the point $Density = 157$. It means that we have a real U-shaped curved. For the small number of listing in the neighborhood *Density* has a negative effect, while it becomes positive at some point. At the same time in Table 4 we can observe reversal U-shaped dependence. Probably omitted variables are responsible for this change, but the exact reason should be explored more carefully.

In regression (4) we studied the effect of prices across the types of houses. It turns out to be significant only for one type of house compared to apartments. Only for row houses, the additional Airbnb listings are associated with an increase in property prices.

5.3 Spatial Autoregressive Model (SAR)

The effect of density in SAR model turns out to be 2 times lower than those which were obtained via IV estimation. Coefficient for density is 0.00024 with z-Statistic equaled 4.738. P-value turned out to be 0.000002. Controls were the same as in the Bartik IV estimation. Table 7 represents the coefficients obtained via SAR estimation (note that p-values are in the brackets).

5.4 Survival Analysis

In Table 8 we see results for survival analysis estimations. We used 2 models for survival analysis: semi-parametric Cox model and non-parametric survival model with Weibull distribution. In regressions (1) and (2) we estimate simple Cox and non-parametric models. In models (3) and (4) as regressors were used predictions of density, regressed by instrumental variable (Bartik IV, the same as we used before) and controls. In regressions (5) and (6) we add controls for rectangles (see as we divided the city into rectangles in 4.4.3). Overall in (1), (3), (5) we estimate Cox and in (2), (4), (6) we estimate parametric Weibull.
It founds out that density of Airbnb listings lowers the time for apartment selling, owners spend less time for selling their houses in the presence of Airbnb listings. After instrument was applied we observe negative significant coefficients, which means that homeowners needed to wait longer for their apartment to be sold. Asking price increases time for transaction. Additionally, good maintenance quality and being monument also accelerates time for selling the apartment.

Table 6: IV estimation

Dependent variable:	Density (1)	ln Price (2)	ln Price (3)	ln Price (4)
Variables				
Instrument	3.856009***			
	(35.46)			
Density		0.000403***	-0.00499***	0.000377***
		(6.74)	(-5.85)	(6.37)
Density^2			0.0000158***	
			(6.71)	
Distance	0.0312262***	0.0000247***	0.0000586***	0.0000256***
	(66.50)	(10.97)	(8.03)	(11.49)
Type 2 × Density				0.000458***
(row house)				(5.15)
Type 3 × Density				0.000279
(semi-detached)				(1.16)
Type 4 × Density				0.000963*
(corner house)				(2.48)
Type 5 × Density				0.000401
(two under one roof)				(0.62)
Type 6 × Density				0.000253
(detached house)				(0.33)
Center	86.46253***		1.044***	
(dummy)	(14.97)		(18.47)	
ln Size	-11.2415***	0.785***	0.790***	0.784***
	(-10.11)	(233.96)	(132.14)	(233.46)
Garden	2.023078*	0.0674***	0.0650***	0.0696***
	(3.10)	(37.72)	(20.07)	(38.21)
Parking	-9.304668***	0.0518***	0.0481***	0.0526***
	(-10.27)	(16.89)	(11.75)	(17.04)
Monument	-10.69116**	0.0453***	0.0664***	0.0440***
	(-7.97)	(11.13)	(9.80)	(10.76)
Fixed-effects				
Time FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Quality	Yes	Yes	Yes	Yes
Type and House configuration	Yes	Yes	Yes	Yes
Construction period	Yes	Yes	Yes	Yes
Fit statistics				
N	62419	62419	62419	62419

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: SAR

parameter	SAR
Distance	0.000 (0.284)
Density	0.0002*** (0.000)
Garden	0.125*** (0.000)
Size	−0.154** (0.021)
W	0.144*** (0.000)

Controlling for spatial lags in (5) and (6) compared to (3) and (4) increased significance of results.

Table 8: Survival analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	T-o-M	T-o-M	T-o-M	T-o-M	T-o-M	T-o-M
Variables						
Density	0.000333***	0.000492***				
	(4.58)	(6.80)				
$\widehat{\text{Density}}$			-0.000810*	-0.00140***	-0.000893*	-0.00155***
			(-2.22)	(-3.86)	(-2.42)	(-4.23)
ln asking Price	-0.791***	-1.118***	-0.748***	-1.048***	-0.775***	-1.091***
	(-26.64)	(-37.45)	(-22.92)	(-31.92)	(-23.32)	(-32.59)
ln Size	0.394***	0.523***	0.352***	0.454***	0.367***	0.476***
	(12.93)	(17.17)	(10.55)	(13.64)	(10.87)	(14.11)
Distance	0.0000477***	0.0000784***	0.0000944***	0.000156***	0.000103***	0.000169***
	(4.69)	(7.70)	(5.35)	(8.87)	(5.75)	(9.51)
Garden	0.0949***	0.137***	0.0944***	0.136***	0.0954***	0.138***
	(7.96)	(11.48)	(7.91)	(11.40)	(7.96)	(11.52)
Parking	-0.0208	-0.0368	-0.0345	-0.0593**	-0.0255	-0.0463*
	(-1.11)	(-1.95)	(-1.78)	(-3.06)	(-1.29)	(-2.34)
Quality	0.0130***	0.0149***	0.0113***	0.0120***	0.0116***	0.0123***
	(4.51)	(5.09)	(3.82)	(4.03)	(3.92)	(4.10)
Monument	0.0738**	0.116***	0.0622*	0.0963***	0.0639*	0.101***
	(2.88)	(4.53)	(2.41)	(3.72)	(2.47)	(3.88)
Fixed effects						
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Type of house	Yes	Yes	Yes	Yes	Yes	Yes
House configuration	Yes	Yes	Yes	Yes	Yes	Yes
Construction period	Yes	Yes	Yes	Yes	Yes	Yes
Location rectangles	No	No	No	No	Yes	Yes
Fit statistics						
Weibull statistics		0.0399***		0.0398***		0.0431***
		(13.42)		(13.38)		(14.46)
N	55, 838	55, 838	55,838	55,838	55,838	55,838

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6 Discussion and policy implications

In general our finding is that Airbnb has dual effect on the housing market of Amsterdam. From the one point it provides additional sources of income for owners of the houses. From the other point it adds rigidity to the housing market: prices increases, sellers become more unwilling to sell the houses. It affects the welfare of long-term residents and newcomers. In long-term it can negatively affect the economic development of the city pushing away potential migrants.

In the context of all of the above we think that city administration should implement some measures to protect the long-term renters. Such measures may include some limitations on short-term rent or subsidies to long-term renters. As tourists are main part of short-term renters, tourist tax may also be useful.

7 Conclusion

In the paper, we analyze the effect of Airbnb listings on the price. We utilized a Bartik instrument consisting of Google Trends and attractiveness to tourists that was proxied by the number of tourist spots near each house. Our regressions show that the number of listing positively affects the price of houses. However, this influence is not monotonic. Instead, we get U-shape dependence with the apex in point 157. The explanation for this surprising effect should be explored more.
We found that type of house matters for the effect of Airbnb. However, in IV regression interaction effect is positive and significant only for row houses.
Additionally, we utilized Spatial Autoregressive Model to use the fact that there is a correlation between units that are located in the vicinity of each other. The effect of density is positive on prices of houses and robust in our specifications.
To estimate the effect of the Airbnb on other sides of the housing market, we use survival analysis. We find, that despite the general increase of time-on-market, Airbnb negatively affects (increases) time-on-market. We think this effect is due to higher opportunity costs for owners, that allows them to be more patient when selling their house.

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