To regulate or to deregulate: effect of Airbnb activity on the Amsterdam housing market

Econometric Game 2021

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As a top tourist destination, Amsterdam draws millions of tourists every year, of which many use Airbnb to find their stay. However, at the same time there is a housing shortage in Amsterdam, which led to increasing housing prices in the last years. It is a priori not known if the increase in Airbnb activity has an effect on housing prices, and if it exists, whether it is positive or negative. Therefore, this paper investigates the effect of Airbnb activity on housing prices in Amsterdam. We use several approaches to estimate this effect taking into account potential endogeneity problems. We find that in general, an increase in Airbnb activity leads to an increase in housing prices. Moreover, the impact is different for the period before 2014 and after, when a change of regulation was made, which made it easier to list a property on Airbnb. The effect is more than 5 times stronger for the period after this change in legislation. To put the size of the effect for the period after 2014 in perspective, its absolute size is larger than half of the size of the Time-on-the-Market, which is a variable that is a priori expected to have a strong impact on house prices. This shows that legislation has a clear impact on the house prices in the short run.

1 || Introduction

In this paper, we analyze the effect of the number of Airbnb listings on house prices in Amsterdam. Amsterdam is the top tourist destination in the Netherlands, drawing millions of tourists every year. Many of these tourists use Airbnb to find their stay in Amsterdam. However, there is a housing shortage in Amsterdam, putting pressure on policy makers to pass legislation to ensure housing in Amsterdam is used for residents, not tourists.

Proponents of stricter legislation for the use of homes for short term rentals on Airbnb make the argument that more homes on Airbnb means fewer homes are sold to residents. Economic theory then suggests that the inelasticity of housing supply in the short run would cause an increase in the prices of houses. This argument is supported by the fact that the development of the number of Airbnb listings and house prices in Amsterdam have followed very similar trajectories since the first Airbnb listing appeared in Amsterdam in 2008. Since 2008, the number of listings has grown exponentially. This is demonstrated in Figure I, which shows that there were only a few listings in 2008 and 2009, but in 2013 the amount increased dramatically and they appeared in all parts of the city. Finally, the number of listings grew even further by 2018. Furthermore, in Figure II, we demonstrate the dynamics of the housing prices. We observe that the prices slightly rose after 2008, right after the introduction of Airbnb (first dotted red line). After 2013, they continued growing exponentially, which may be associated with Amsterdam City Council policy of making short-term rental easier for the local residents (second dotted red line).[1] We observe this pattern both for houses and apartments types. At first sight, it is not difficult to see why some would argue that the increase in Airbnb listings had caused an increase in house prices in Amsterdam, since the correlation is positive.

However, opponents of stricter regulation could argue that it is also possible that increased short term rentals via Airbnb have a negative effect on prices. For instance, it is possible that increased tourism is a nuisance to residents, hence driving them out of neighbourhoods where Airbnb is prevalent. Mathematically, perhaps without realizing it, opponents of stricter legislation for Airbnb rentals are arguing that the relationship in Figure II might be due to confounding variables affecting both the housing prices as the number of Airbnb listings.

Hence, it is possible to economically argue both a positive and negative relationship between Airbnb listings and house prices. This paper provides an empirical investigation of the nature of the relationship between the two variables in question.

Similar relationships have been investigated in the literature. A recent study by Barron et al. (2021) found that a 1% increases in Airbnb listings lead to a 0.026% growth in house prices in the United States. In a paper by Koster et al. (2018), it was shown that Airbnb had a large effect on house prices in areas attractive to tourists. Garcia-Lópe z et al. (2020) found in their investigation that for the average neighbourhood in terms of Airbnb activity, the house prices increased by 5.3%. However, not much research has been done on Amsterdam housing market which is the main focus of this paper.

The relationship of interest in this paper is the effect of the number of Airbnb listings on housing prices. We start the analysis by estimating a neighborhood and time fixed-effects model with region-specific time trends. The analysis reveals that after controlling for amenities, there is no significant relationship between Airbnb activity and house prices. However, when we take the change in legislation into account and make a difference in effect in the period before 2014 and after, a significant relationship was found for the period after 2014 (+0.016%). Furthermore, we find no strong evidence of a non-linear relationship between Airbnb activity and housing prices.

There are number of ways the relationship between Airbnb activity could be obscured by endogeneity. First, there might be a reverse effect of housing prices on Airbnb listings, causing simultaneity bias. Second, there are possible variables that affect both housing prices and numbers of Airbnb listings. For instance, population growth or GDP growth could positively affect both house price and listings. To tackle these sources of endogeneity we use an instrumental variables approach. The instrumental variable we use is an interaction (product) between a measure of how 'touristy' a postal code is and a measure of the interest in Airbnb. Firstly, as a measure of how 'touristy' a postal code is, we use the density of monuments (such as parks, musea or statues) in that postcode. The validity of the instrument is based on the fact that having monuments nearby matters to tourists, thus effecting Airbnb listings, but does not matter to local residents, hence not affecting house prices which is reasonable. Secondly, we use Google

[1] https://www.airbnbcitizen.com/wp-content/uploads/2016/12/National_PublicPolicyTool-ChestReport-v3.pdf

trends to measure the interest in Airbnb. Clearly, higher interest in Airbnb through Google searches is a valid proxy for the amount of Airbnb listings made. And due to the fact that the changes in Google searches will most likely be due to changes in popularity and not changes in housing prices, Google searches for Airbnb is a valid instrument.

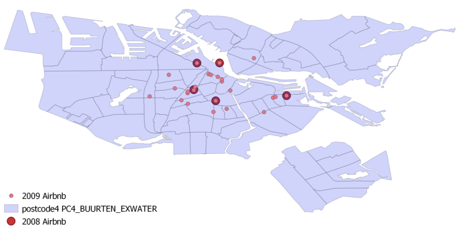
The results of the instrumental variable approach are stronger compared to the approach without instrumental variables. The effects of Airbnb activity on housing prices when not making a distinction in effect before and after the policy change is (+0.085%) in the 2SLS case. When making the distinction between the periods before implementation of the regulation change and after, we find that there is an effect both before the regulation change (+0.112%), and after (+0.0669%) for the 2SLS estimation.

This decrease in effect after the regulation change is somewhat surprising. However, this regression considers the actual sale price, which can be regarded as an equilibrium between buyers and sellers. These equilibria are determined simultaneously with the Time-on-the-Market (TOM). This variable measures how many days a house was listed before it was sold. This can be considered as a source of friction, as sellers need some time to match with potential sellers. We therefore include the TOM as a dependent variable to explain house price. However, doing this introduces another source of endogeneity, as the TOM and transaction prices are determined simultaneously and they are subject to the unobserved components such as the (in)patience of the seller and buyer. To resolve this source of endogeneity, we use two-stage SUR approach as in Dubé and Legros, 2016 by using spatiotemporal instruments which are based on the averages of the lagged ask prices, lagged number of transactions, lagged transactions prices and lagged TOM within a given district. This SUR analysis shows that Airbnb activity has a overall positive impact on house prices in Amsterdam. Moreover, this effect is strongly amplified after 2013. The effects are 5 times as large after the introduction of more lenient legislation, furthermore these Airbnb effects on the housing market are also large relative to other important factors such as TOM. To put the effects in perspective: if the growth in Airbnb searches on google would continue as it did in the period from the end of 2013 to the end of 2018, this would lead to an increase of the house prices by about 0.066% per year.

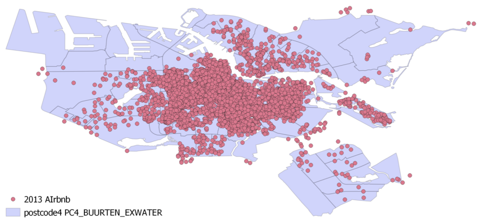
The structure of the paper is as follows. In Section 2, we introduce the data, discuss the instruments and describe the transformations required for the subsequent analysis. In Section 3, we explain the methodology that we use to identify the causal effect of the Airbnb. In Section 4, we describe and interpret the results. Finally, Section 5 concludes. We also discuss there policy implications of the analysis and suggestions for future research.

2 ‖ Data

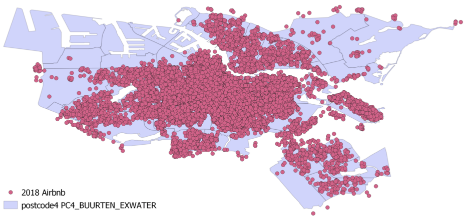
The data comes from the Dutch Association of Realtors (NVM) and contains microdata on housing prices in Amsterdam for the period 2000-2018. Specifically, it contains transaction housing prices as well as housing characteristics at the address level. We consider housing prices as a dependent variable. The main independent variable of interest is the Airbnb activity in Amsterdam. There are several ways to measure this activity. First, we focus on the number of the Airbnb listings within a radius of 250 metres, since the more listings there are the more



(A) 2008 and 2009



(B) 2013



(C) 2018

FIGURE I

Airbnb listings at different points in time

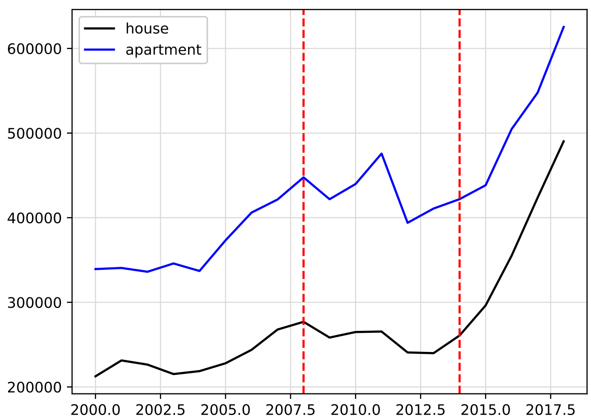


FIGURE II

Housing prices dynamics for different types of housing

Airbnb can potentially affect the house prices (if there is any effect present). Next, we consider the distance to the nearest Airbnb listing as an Airbnb activity measure since the prices of the houses that are located closer to the Airbnb places might be affected more.

2.1 ‖ Control variables

The housing prices are usually modeled using hedonic regression which models housing prices as being a composite of several housing characteristics. This approach is based on the consumer demand theory and was originally proposed by Rosen, 1974. Therefore, in the main regressions we always control for the housing characteristics that are usually related to the housing prices. Particularly, we control for the size, year of construction, whether there is parking and garden, type of the housing, quality of house and monumental status. Moreover, we include buyerpaysor-free variable as a covariate since it can affect the housing price. In the original dataset, we also had three variables that characterize the size of the apartment: size, volume, and number of rooms. Since these three variables are highly correlated to avoid multicollinearity problem we focus only on size as a covariate since it is related both to volume and number of rooms.

2.2 ‖ Data transformations

We take the logarithm of the housing prices as it is usually done in hedonic regressions. Moreover, to make large observations less influential we also work with the logarithm of the Airbnb measures and logarithm of the size. In Figure III, we demonstrate the result of the transformation for the transaction price where it can be seen that the distribution is less skewed. Furthermore, we transform the variable *quality* into four categories: "bad", "poor", "good" and "excellent". Initially, the variable quality is between 0 and 20, then "bad" quality corresponds to the 1 percentile, "poor" to the 1-10 percentile, the majority corresponds to "good" quality (10-90 percentile) and top 10 observations correspond to the "excellent" group. Additionally, since tourists rent apartments more often than houses we expect that Airbnb had a different effect on the apartment and houses prices houses. However, we do not expect the effect to be different for different types of houses. Therefore, we transform the variable type into house and accommodation type (0 and 1).

In Table I, we report the descriptive statistics for all the variables in the dataset taking into account that we have transformed quality and type variables (other variables are not transformed yet). As can be seen in Table I, there are a few outliers with regard to the asking price, which are implausibly high (more than twenty standard deviations away from the sample average). We therefore omit these observations. We also exclude housing prices that are larger than 1,000,000 euros from the further analysis since these type of houses are less likely to be affected by the Airbnb activity or it can also bex a measurement error in the dataset.

2.3 ‖ Instrumental variables

2.3.1 ‖ *Instrumental variables for Airbnb density*

To resolve the endogeneity issue we construct an instrumental variable, which is an interaction of two components: monuments per square kilometre in a postal code district (four digits) and

TABLE I

Summary statistics

	Mean	Sd.	min	max	Q_1	Q_2	Q_3
final transaction price	301037.2	228096.8	50000	2500000	173843.5	235000	340000
time on market in days	117.1617	183.0441	0	3822	22	53	134
asking price	330843.1	4308655	25000	1.00e+09	179000	240000	349000
dist. to nearest AIRBNB list.	274.7201	882.6412	0	8842.936	0	17.26837	78.31628
# of AIRBNB list. within 250m	44.00041	90.55371	0	685	0	0	37
construction period	4.195232	2.694488	1	9	2	3	7
garden present	.2731649	.4455869	0	1	0	0	1
size in m2	86.65989	42.89216	25	1185	60	76	100
volume of house in m3	245.9992	141.8532	55	4740	162	210	283.5
number of rooms	3.247897	1.386662	0	103	2	3	4
apartment indicator	.8640262	.3427623	0	1	1	1	1
parking available	.1039838	.3052409	0	1	0	0	0
status as a monument	.0311509	.1737261	0	1	0	0	0
bad quality	.008235	.0903727	0	1	0	0	0
poor quality	.0794356	.2704187	0	1	0	0	0
good quality	.7950756	.4036482	0	1	1	1	1
excellent quality	.1172538	.3217239	0	1	0	0	0

Note that we report the summary statistics for the initial dataset which contains outliers.

the interest over time in the google search term "Airbnb Amsterdam".

The first component, the number of monuments per square kilometre in a postal code district is publicly available on the Amsterdam municipality website[2]. These include monuments like statues, musea, and parks. We use this component as it is varies across the different postal codes in Amsterdam, and it is not correlated with the house prices. Using the software QGIS we generated the density of the monuments per $\mathbf{km^2}$ per postal code district (Figure IV).

Second, we also consider the interest over time index in the google search "Airbnb Amsterdam"[3]. This index represents search interest relative to the highest point, which is set to 100. This index is depicted in Figure V. As can be seen, the raw data is rather spiky and a bit erratic as a signal. This is potentially because the moment of searching for an Airbnb accommodation may not be the same as the moment of going to Amsterdam. To estimate a clearer signal, we use a Kalman exponential smoother in a state space model (Durbin and Koopman, 2012):

$$google_t = \mu_t + \epsilon_t, \qquad \epsilon_t \sim \mathcal{NID}(0, \sigma_\epsilon^2) \tag{1}$$

$$\mu_{t+1} = \mu_t + \eta_t, \qquad \eta_t \sim \mathcal{NID}(0, \sigma_\eta^2) \tag{2}$$

$$\mu_1 \sim \mathcal{N}(0, \kappa), \qquad \kappa \to \infty \tag{3}$$

We then use an interaction of these two components to obtain an instrumental variable. Since we work with the logarithm of the Airbnb activity we use the logarithm of the Google trend search.

[2]`https://maps.amsterdam.nl/open_geodata/?k=122`. From this dataset, we excluded the houses listed as monuments, as these may be correlated with house prices.

[3]`https://trends.google.com/trends/explore?date=all&q=airbnb%20amsterdam`

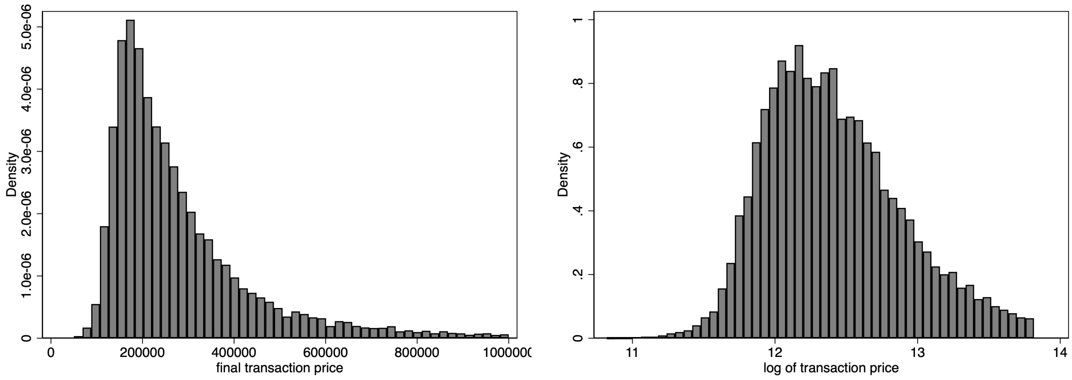


Figure III

Histogram of the transaction price (left) and logarithm of the transaction price (right).
Note that we only report house prices that are smaller than 1,0000,000 euros.

2.3.2 ‖ *Instrumental variables for Time-on-the-Market and Transaction prices*

We also construct instrumental variables for the dependent variables which are the logarithm of TOM and logarithm of the transaction prices. We describe the model itself in the next section. Here, we use the method described in (Dubé and Legros, 2016) to construct instrumental variables. The instrumental variables are based on the averages of the lagged ask prices, lagged number of transactions, lagged transactions prices and lagged TOM within a given district. Therefore, the instruments are based on the past and exogenous information. For each 4-digit postal code, we consider the log(average number of transactions + 1), log(average transaction price), log(average ask price), log(average time on market + 1) (we add 1 in order to avoid taking logs of zeros) in the two years prior to the year of the dependent variables. The choice of the 2 year window was made to account for backward looking behavior, however, we expect it to be limited therefore we use relatively small window. We opt for 2 year instead of 1 year since for some districts there were no transactions in some years, hence we balance the loss of observations for the these years and the loss of observations for postal codes for which no transactions took place in the prior years. As a result, we drop a limited amount of the postal codes. However, they represent a low number of transactions (1742 transactions) and hence do not affect the validity of our analysis.

3 ‖ Models

3.1 ‖ Baseline Model

Our baseline specification is the following:

$$log(Y^r_{it}) = \alpha_r + \tau_{year} + \beta log(Airbnb^r_{it}) + \rho_r t + \rho_r t^2 + \gamma_i X^r_{it} + \epsilon^r_{it}, \tag{4}$$

where Y^r_{it} transaction price of house i which is located in region r, α_r are region-specific fixed effects that account for time-invariant region characteristics, τ_{year} are yearly time fixed effects that are common to all the areas, and X^r_{it} are housing characteristics. We also include region-specific quadratic time trend to account for different time trends in different regions. $Airbnb_{i,t}$

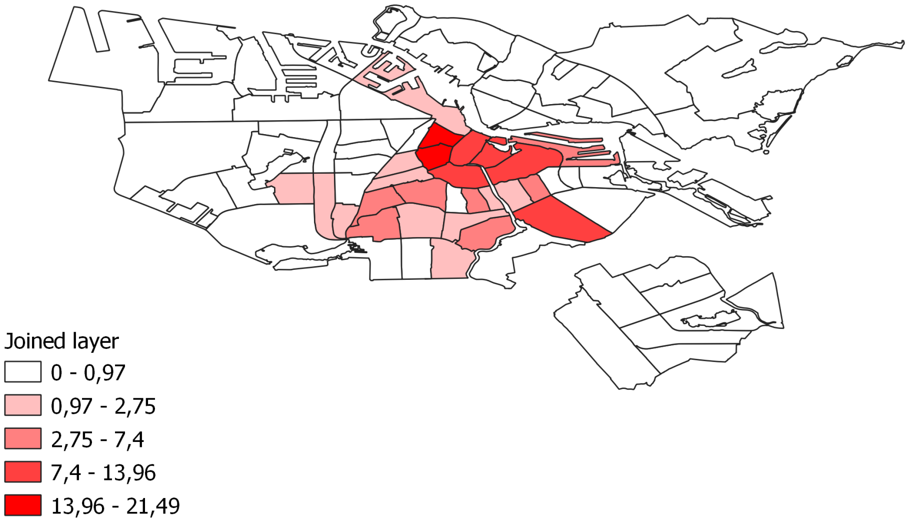


Figure IV

Monuments per square kilometer per four-digit postcode

is a measure of the Airbnb activity which is measured either using distances or density. This is Model (1). The regions are defined based on the $pc4$ zip code level and the standard errors are clustered at the region level.

Furthermore, in 2014 the Amsterdam City Council made it more accessible for the residents to share their private apartments on platforms like Airbnb. Therefore, we expect that the effect of Airbnb to be larger after 2014. Hence, we consider a modified version of the baseline specification with an additional term $\tilde{\beta} log(Airbnb^r_{it}) \times D_{t>2014}$, where D is equal to 1 after and including 2014 year (Model 2).

As there could be some nonlinear effects of the Airbnb activity on the house prices we further consider the baseline model with additional nonlinear terms: $log(Airbnb^r_{it})^2$ and $log(Density^r_{it}) \times log(\frac{1}{Distance^r_{it}})$ as regressors (Model 3).

3.2 || Instrumental Variable Model for Airbnb Listings

The causal graph for the effect of Airbnb listings on the housing price is given below in Figure VI. We wish to investigate the effect of the number of Airbnb listings on the housing prices. However, there might be numerous causal paths making the analysis of this effect problematic.

First, there could also be a reverse effect between the dependent and independent variables, resulting in simultaneity. It is very likely that the house prices in a district have an effect on the number of Airbnb listings. High house prices could cause landlords to sell their property, lowering supply of the Airbnb apartments, or an increase in the house prices could be associated with an increase in the rental price which consequently could lead to the increase in the Airbnb activity. Additionally, there could be numerous confounding variables, such as the population

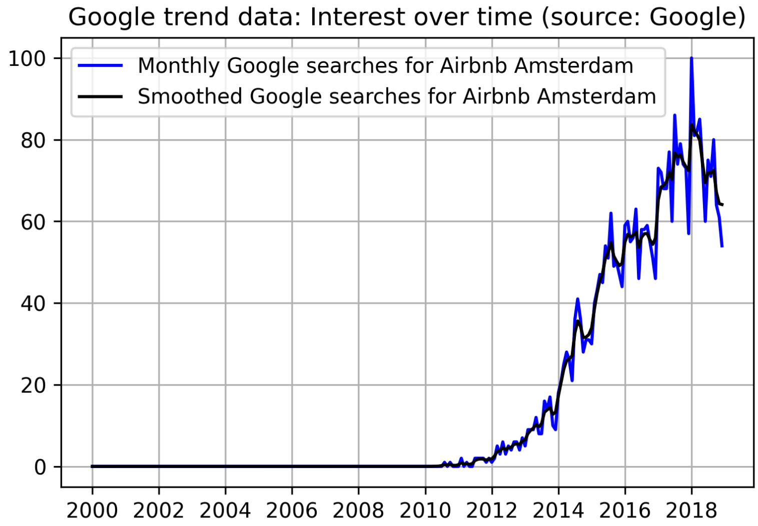


Figure V

Interest over time in "Airbnb Amsterdam: raw data and smoothed estimate"

of a city. An increase in the population could lead to both an increase in housing prices and an increase in rental offerings. Moreover, in general, it is hard to measure Airbnb activity since some listings can be present on the website but not be active and it is also hard to measure the distance accurately. So, we expect a measurement error to be present which leads to the endogeneity problem as well.

Given that it is very likely that there is an endogeneity issue. We think it is important to account for it in this study. One way to address the endogeneity issue could be to run a natural experiment to isolate the effect of the Airbnb on the housing prices by not allowing Airbnb activities in particular regions. However, we do not have this option in real life. Therefore, another possibility would be to conduct a quasi-experiment as it was done, for example, in Koster et al., 2018.

Since we do not have the above mentioned natural and/or quasi experimental setups, we therefore opt for the instrumental variable approach. The instrumental variable serves as a means of isolating the effect of the number of listings on house prices. To successfully accomplish this task, it is important that (i) the IV correlates with the Airbnb activity measure and (ii) the IV does not correlate with the housing price. If this is the case it means that the instrument is (i) relevant and (ii) valid.

The number of Google searches for Airbnb in Amsterdam has grown over the measurement period, and as described in the data section, it is plausible that it is correlated with Airbnb listings, but not with house prices, making it a relevant and valid instrument. Also, we consider the density of monuments per square kilometer per postal code. As we assume that tourists enjoy being near the sights, the monument density will effect the Airbnb activity. Furthermore, we assume that the monument density will not affect housing prices, since local residents are less influenced by their proximity to these kind of monuments in general. The combination of both the described assumptions makes monument density a valid and relevant instrument.

To create a variable that runs over the different districts and time periods, we combine the two instruments described in the previous paragraph by multiplying them.

Note that we do not include the district-specific time trends in the second stage when using this IV approach since it captures similar pattern as the instrument does.

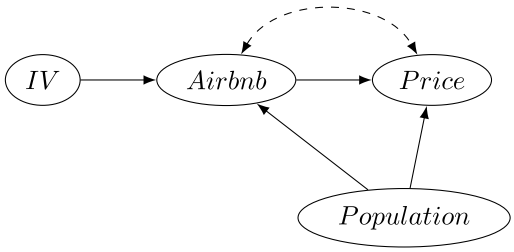


Figure VI

Causal graph

3.3 || Simultaneous Transaction Price and Time-on-the-Market Problem

The Time-on-the-Market (TOM) variable provides useful information about the transaction price of a house. However, the inclusion of this variable adds another source of endogeneity due to simultaneity. Intuitively, the transaction price reveals the equilibrium price that was established between the buyer and seller. However, it takes some time for the seller to find the buyer, hence the initial (ask) price could be different from the final transaction price. The decision about the transaction price and time on the market is made simultaneously – the seller wants to spend less time on the market but also to maximize his profit from selling the house. The patient seller can wait longer hoping to sell for the higher price while some buyers may prefer to sell it quickly but for a lower price. This also demonstrates that the TOM and the final transaction prices depend on the seller characteristics such as patience and motivation which are usually unobserved. Moreover, it depends on the buyers motivation which is also unobserved. Therefore, the motivation of the actors is hidden and affects both variables. We schematically illustrate the causal graph in Figure VII. To account for the TOM effect on the housing prices, we then need to resolve the endogeneity issues.

We account for this using approach proposed by Dubé and Legros, 2016. We use a two-stage approach based on the instrumental variables to resolve the endogeneity problem. Moreover, we estimate equations simultaneously using a seemingly unrelated regression equations (SUR) model.

4 || Results

4.1 || OLS Regression

Table II reports the results of the OLS regression of the log(transaction prices). The first column is a regression on the log(density), where we consider both zip code, year fixed effects and region-specific trends, and further control variables which are described in the Section 2. In

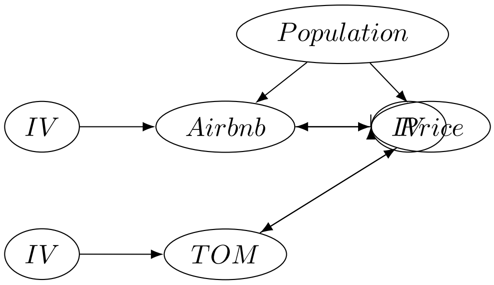


Figure VII

Causal graph when Time-on-the-Market variable is included in the analysis

this regression, an increase of 1% in the density leads to an increase of 0.007% in house prices. However, the relationship is statistically insignificant.

The regression in the second column additionally considers different slopes for the period before the change in regulation in 2014, and afterwards, by the inclusion of a dummy variable. In this regression, all fixed effects and controls are the same as in the first regression. We notice that the slope steepens quite substantially after 2014, when Amsterdam implemented more lenient regulations regarding Airbnb renting. As a consequence, the slope of the log(density) is non-significant before 2014, and then jumps up. In this regression, an increase of 1% in the density leads to an increase of 0.020% in house prices in the years following more lenient legislation in 2014, whereas the increase was non existent when regulations were stricter in the preceding period. This clearly shows the potential impact of legislation on the short-run impact of Airbnb on the housing market.

The third regression considers two more variables: the product of the log(density) and $\log(\frac{1}{distance})$, as well as the $\log(\text{density})^2$. Here as well, the fixed effects and controls are the same as in the other regressions. Again, the log(density) before the change in regulation in 2014 is not significantly different from 0, whereas the log(density) after the change in regulation is. In this case, an increase of 1% in the density leads to an increase of 0.016% in house prices in the years following more lenient legislation in 2014 (not taking into account the insignificant effect from before 2014). Therefore, the difference in the effects before and after the regulation change in 2014 seems to be robust.

All three regressions imply that there is no significant relationship between the number of Airbnb listings within a 250 metre radius and house prices in the years before the legislation change in 2014. However, models (2) and (3) indicate that the policy measure conducted by local government in 2014 caused the number of Airbnb listings to significantly impact house prices in a positive way. This indicates a positive relationship between short-term rental policy lenience and house prices. A possible implication of these findings is that a passing legislation making short-term rental more difficult could lower the housing prices.

4.2 || Instrumental Variable Regression

In order to deal with the endogeneity of the Airbnb activity we perform an instrumental variable regression. In this IV analysis we instrument the number of Airbnb listings within 250m of the property with the interaction of the logarithm of smoothed searches for Airbnb Amsterdam and

Table II

Impact of density of Airbnb listings on house prices: OLS estimates

	log(price)		
	(1)	(2)	(3)
log(density)	.007	-.000	-.007
	(.005)	(.004)	(.005)
log(density) × regulation		.020***	.016***
		(.003)	(.004)
log(density) × log(distance^{-1})			-.000
			(.000)
log(density)^2			.002
			(.002)
Zip code fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
R^2	.920	.920	.920
N	108440	108440	108440

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

number of monuments in line with Garcia-López et al. (2020) and Barron et al. (2021). The first component tracks changes in Airbnb activity over time, while the second component captures the proximity of the neighbourhood to the city's tourist amenities. Moreover, when we introduce the nonlinear effect of Airbnb activity on prices, by means of allowing for a slope shift after 2013, we add additional instruments. To account for the interaction effect between the endogenous variable and the legislation change indicator we introduce linear and quadratic transformations of the instrument and the legislation indicator as outlined in Bun and Harrison (2019).

Table III shows the IV regression output estimates by the 2SLS with clustered standard errors at the zip code level. In the first stage regression we find no evidence for potential weak instrument problem as the F-statistic is $16.34 > 10$. From the second stage estimation we observe that the sign compared to the OLS estimates has not changed. Similar to the neighbourhood and time fixed effects models estimated by OLS discussed above, we included neighbourhood and time fixed effects as well as a large group of control variables capturing a large variety of housing characteristics for both IV regressions.

When comparing the first 2SLS model (first two columns) with the first OLS model, it is quite noticeable that the 2SLS regression reports that an increase of 1% in the density leads to an increase of 0.08539% in house prices, whereas in table II the same relationship did not yield a significant increase. This indicates that our OLS estimates had a strong bias towards zero, due to the endogeneity of the Airbnb listing variable. When including also the $log(density) \times regulation$ term, which changes the slope for the period after 2014 (after change in regulation), both log(density) and $log(density) \times regulation$ are significant. As a result, an increase of 1% in the density leads to an increase of 0.11226% in house prices in the period before the regulation change of 2014, and to an increase of 0.0669% in the period after this regulation change. Again, these respective effects are much larger than in the OLS regression, where there was no significant effect found for the period up to 2014, where an increase of 1% in the density led to an increase of 0.016%.

It is surprising that $log(density) \times regulation$ has a negative coefficient, which implies that in the period after the change of regulation, the effect of density of Airbnb listings has a smaller impact on housing prices than before. However, it should be noted that by using that the house prices used in this regression are equilibrium prices, which are determined simultaneously with the Time on Market. Therefore, by using a simultaneous equation approach, it is possible to disentangle these two effects. This is discussed in the next section.

4.3 ‖ Disentangling Sale Price and Time-on-the-Market

Table IV shows the results of the two-stage approach using SUR and instrumental variables based on lagged spatio-temporal averages of sales prices, number of sales, time-on-the-market, and ask prices as introduced in Dubé and Legros (2016). This methodology allows us to jointly model the determination of prices and time-on-the-market. Moreover, this allows us to disentangle the effects of Airbnb activity on both the prices and time-on-the-market.

From the first-stage regression we observe that our estimates for the logarithm of prices are in line with the ones found by Dubé and Legros (2016). However, for the results from first-stage regression for the logarithm of time-on-the-market differs from that of Dubé and Legros

Table III

Impact of density of Airbnb listing on house prices: IV estimates

	First stage	Second stage		First stage	Second stage
	log(density)	log(price)	log(density)	log(density) $\times$ regulation	log(price)
instrument	.00001***		.00002***	.00000***	
	(.000)		(.000)	(.000)	
log(density)		.08539***			.11226***
		(.009)			(.022)
instrument $\times$ regulation			.00044***	.00071***	
			(.000)	(.000)	
instrument^2			.00000***	.00000***	
			(.000)	(.000)	
instrument^2 $\times$ regulation			-.00000***	-.00000***	
			(.000)	(.000)	
log(density) $\times$ regulation					-.04536**
					(.021)
Zip code fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
R^2	.88550	.91304	.88938	.90774	.91037
N	108440	108440	108440	108440	108440

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(2016). We find that the spatio-temporal instrumental variable based on time-on-the-market has no significant effect on time-on-the-market itself. This could potentially be due to the choice of spatial and temporal windows to base the instrumental variables on. Nonetheless we find that both F-statistics of the first-stage regressions are well above 10, so we find no evidence for a weak instrument problem.

From second stage results of the IV SUR model in Table IV we observe that by disentangling time-on-the-market and sales price we find a positive relationship between Airbnb activity and moroever a strong amplification of this positive effect after the legislation change in 2014. After 2014 the effect is more than 5 times as large compared to before 2014. After it was made easier to use Airbnb in Amsterdam a 1% increase in Airbnb activity in a range of 250m of the property would yield on average an increase of .1% in housing prices. This shows a strong effect of legislation on the impact of Airbnb activity on the housing market. This is in contrast with the earlier described IV results. This difference can be explained by the fact that after disentangling the effect from time-on-the-market on price formation in equilibrium, we measure the effect of Airbnb activity on prices corrected for potential search frictions. To put these Aribnb effects into perspective, we observe from our SUR estimation results that the Airbnb activity effect on prices after 2013 is more than half of that of time-on-the-market. This highlights the potential impact Airbnb can have on house prices as time-on-the-market is a important factor in determining house prices in equilibrium.

4.4 ‖ Robustness Analysis

These results are not driven by the specific choice of the variable capturing Airbnb activity. In the appendix we show the OLS and IV estimation results in the case when we use as a measure of Airbnb activity the distance to the closest Airbnb listing. From Tables .V and .VI in Appendix we observe that the same results apply using this different measure of Airbnb activity, strengthening the robustness of our core results.

5 ‖ Conclusion

This paper analysed the effect of Airbnb activity on housing prices in Amsterdam. We find a significant effect of the Airbnb activity on the house prices since Airbnb entered the Amsterdam market. Moreover, after regulation was introduced by the local government in 2014 that simplified the short-term rental we observe a strong amplification of this relationship. More specifically, after the introduction of the new legislation the effect of Airbnb activity on house prices increased 5-fold. The Airbnb activity effect on prices after 2013 is more than half of that of time-on-the-market, this highlights the potential impact Airbnb can have on house prices as time-on-the-market is a important factor in determining house prices.

We introduced an instrumental variable and a SUR model, accommodating possible endogeneity of the variables and simultaneity issues, to identify the effects of Airbnb activity on the housing market. We conclude that increases in Airbnb activity lead to substantially higher housing prices in Amsterdam, especially since the change in regulation in 2014. Hence, we find clear evidence that legislation has a strong impact on the housing prices in the short run.

Table IV

Impact of distance to nearest Airbnb listing on house prices: SUR estimates

	First stage		Second stage	
	log(price)	log(TOM)	log(price)	log(TOM)
IV log(price)	1.89393***	-2.76167***		
	(.304)	(1.022)		
IV log(TOM)	-.00448	.08698		
	(.015)	(.055)		
IV log(number of sales)	.02184**	-.13794***		
	(.009)	(.044)		
IV log(ask price)	-1.40464***	3.05867***		
	(.313)	(1.035)		
log(density)			.01829***	.08787***
			(.004)	(.024)
log(density) × regulation			.08405***	.42314***
			(.005)	(.028)
log(TOM)			-.18908***	
			(.006)	
log(price)				-5.00241***
				(.124)
Zip code fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
R^2	.66944	.15994	.76100	-.12143
N	101531	101531	101531	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To extend the analysis presented in this paper one can also account for the effect of the macroeconomic environment on the house prices. For example, changes in population or in GDP could also have an influence on housing prices. The effect of including these variables in the respective models can be investigated. Another suggestion for further research consists of comparisons of neighbourhood bans on Airbnb rentals. In 2020, Airbnb was forbidden in three neighbourhoods of Amsterdam [4]. Although this ban on Airbnb rentals was recently lifted by court order [5], it can be expected that such further experiments may take place. When this happens, local differences between neighbourhoods with such a ban or restriction and neighbourhoods without could be investigated.

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Appendix

Table .V

Impact of distance to nearest Airbnb listing on house prices: OLS estimates

	log(price)		
	(1)	(2)	(3)
log(distance)	-.003	.001	.026***
	(.002)	(.003)	(.005)
log(distance) × regulation		-.009***	-.023***
		(.003)	(.005)
log(density) × log(distance^{-1})			-.001
			(.001)
log(distance)^2			-.002***
			(.001)
Zip code fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
R^2	.920	.920	.920
N	108440	108440	108440

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table .VI

Impact of distance to nearest Airbnb listing on house prices: IV estimates

	First stage	Second stage	First stage		Second stage
	log(distance)	log(price)	log(distance)	log(distance) × regulation	log(price)
instrument	-.00001***		-.00001**	-.00000***	
	(.000)		(.000)	(.000)	
log(distance)		-.16462***			-.14785***
		(.018)			(.022)
instrument × regulation			-.00005	-.00032***	
			(.000)	(.000)	
instrument^2			-.00000	-.00000**	
			(.000)	(.000)	
instrument^2 × regulation			.00000	.00000***	
			(.000)	(.000)	
log(distance) × regulation					-.04123**
					(.020)
Zip code fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
R^2	.93310	.88453	.93323	.90489	.88411
N	108440	108440	108440	108440	108440

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$