To what extent does Airbnb affect house prices in Amsterdam?

Team 11

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1 Abstract

The impact of Airbnb has come under significant scrutiny and this short paper contributes to the literature by looking at Airbnb's effect on house prices in Amsterdam. The key issue is identification due to the likely presence of unobserved confounding factors like tourism demand, which shift housing supply and demand in Amsterdam. We employ Generalised Random Forests to estimate a local average partial effect that comes closest to a causal effect of Airbnb on house prices. These results are compared to the benchmark of a panel data model with time- and area-fixed-effects. The estimated average treatment effects show a nuanced picture of the causal effect of Airbnb presence on local housing demand. Further distance to an Airbnb seems to increase house prices by 0.87% for each 100 meters. A 0.019% decrease in house prices per additional listing within 250 meters seems to suggest a counterintuitive negative effect on local house prices (possibly due to negative externalities). The spillover of Airbnb on neighbouring areas' house prices may be positive, which requires further investigation.

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2 Introduction

A Brief background on Airbnb

Airbnb is part of the 'sharing economy' and its motivation is to match short-term rental demand with underutilized houses or spare rooms. Because of Airbnb's review systems, potential renters can screen potential landlords. The reduction in trust and quality assurance frictions should ensure a reduction in unused room capacity and so an increase in economic efficiency. This also allows homeowners to rent out their property for short periods of time and so access a direct income stream from their property which should, other things equal, increase their house value.

The platform uses matching technology to reduce the search costs of users and facilitate smooth and safe transactions with its review and reporting mechanism. Airbnb also opens up new areas to tourism with three-quarters of its listings in neighbourhoods typically not covered by the traditional tourist industry. Meanwhile, it offers an authentic and budget rental option for tourists and short-term visitors.

A Brief background on Airbnb in Amsterdam

Airbnb was first introduced in Amsterdam in 2008 and has grown rapidly since, with one in 15 dwellings in Amsterdam showing up on an online rental platform such as Airbnb in 2020 [1]. This growth has been accompanied by sharp rises in house prices with house prices increasing 65% in the 5 years to 2018. This is not necessarily causal.

A concern with Airbnb would be that it benefits non-resident tourists at the expense of residents, which is clearly a public policy problem. This tension between residents and non-residents culminated in 75% of residents in 3 historic regions voting to ban home-rental although this ban was later overturned.

Channels through which Airbnb affects house prices

Prices are fundamentally the result of a supply and demand relationship which is often ignored in hedonic pricing but it is this relationship that is key to understanding the channels through which Airbnb affects house prices. From this relationship, we know that anything that affects supply or demand can affect the price. This then gives us several clear potential channels as below. These are explored in more detail in the 'Channels' section.

1. A shift from long-term renting supply to short-term renting causing a reduction in long-term renting stock (supply).
2. Airbnb can increase tourism who demand services that require land (supply).
3. An increase in a house's income stream which increases the house value (demand).
4. An increase in the income/wealth of homeowners/other locals increasing ability to pay and so demand (demand).
5. Negative (non-pecuniary) externalities imposed by Airbnb users on locals (demand).

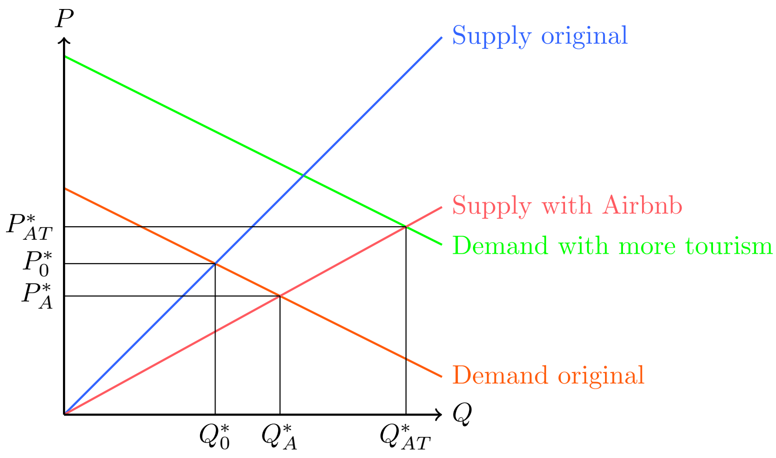
It's important to note that while some of these channels such as the externality channel will primarily be a very localised phenomenon, other channels such as the wealth channel will have much more of a dispersed effect across the Netherlands as landlords do not need to purchase property near their current property and a diversification of risk argument would suggest they may not want to focus their property portfolio in a single area.

Key potential issues

In general, treatment effect identification in a hedonic pricing regression, where the price is modelled as a function of regressors, is challenging. As prices are the result of the equilibrium of supply and demand, any variable that shifts supply or demand also shifts the price. Hence, all variables that would shift the demand or supply equation and are correlated with the treatment effect must be conditioned on. Any of those variables we don't condition on would be unobserved confounders, which would cause bias in the treatment effect estimator. Estimation of the causal effect of Airbnb on house prices faces all these challenges. The most obvious confounder in Amsterdam's short-time rental market is tourism demand. Short-term rentals and tourism are close substitutes. As the demand for tourism increases, short-term rental demand increases accordingly (figure 1). The short-term rental rate increases just like its quantity.

By using time and location dummies we account for this issue.

Figure 1: Short-term rental market with more tourism



Key findings
We initially use panel data methods which suggest that there is a positive effect of distance to the nearest Airbnb on house prices and a negative effect of density of Airbnb's on house prices.

The random forest we subsequently run supports this analysis and obtains predictions that are close to the linear prediction. The random forest also finds that the predicted effect of Airbnb density on local house prices varies widely across the set and so to give a single point estimate for the effect of Airbnb density on house prices would be clearly incorrect. Rather, we have a heterogenous treatment effect with the effect depending on the house's specific characteristics.

We also consider the spatial evolution of house prices and the emergence of Airbnb listings across different regions.

Other's results
Barron et al [3] look to answer the same question but for the United States. They use instrumental variables and conclude that on average a 1% increase in Airbnb listings increases rents by 0.018% and importantly house prices by 0.026%. They conclude this is due to the reallocation of the housing stock by landlords and due to the increase in a house's earning potential.

Sheppard and Udell (2016) [6] examine the effect of Airbnb in New York with a hedonic pricing model and find that a doubling of Airbnb listings is associated with a 6-11% increase in property prices. Other estimation methods they consider produce even higher estimates; their difference-in-difference approach estimates the Airbnb treatment (having an Airbnb listing within 300m) increases value by 31%.

As explained above, it appears the treatment effect is heterogeneous so to claim a single effect due to the presence of Airbnb would be inappropriate. Meanwhile, our results do not seem to support these existing studies.

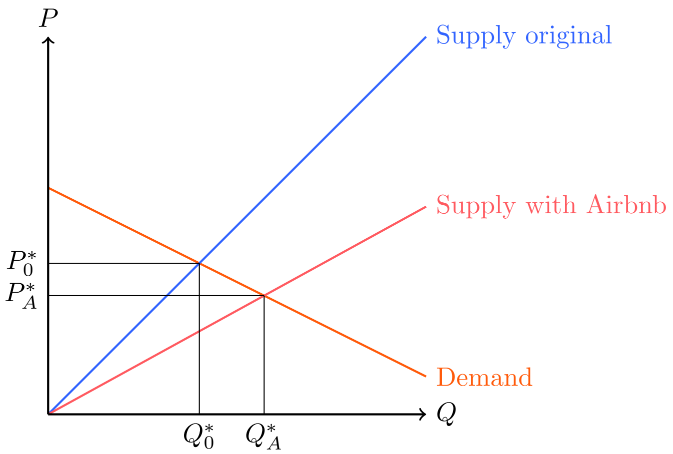
3 Channels

We consider two broad markets: the freehold market and the rental market. The rental market can be further segmented into a short-term rental market mostly for tourists and a long-term rental market for local residents. Hotels, for example, constitute a large part of the short-term rental supply. Short-term and long-term renters have different demands and needs but they both draw from the (same) total housing stock. Traditionally segmentation has existed on the supply side as well as the demand side because of these different needs and because of different legal environments.

The rise of house-sharing is blurring this divide and enables owners of traditionally long-term rental properties to target short-term renters [3]. Airbnb reduces frictions and costs of short-term rental for landlords. These frictions include trust and quality assurance that traditionally would have made short term house rental very difficult [4]. This friction reduction is likely to increase the marginal propensity of homeowners to reallocate housing from the long-term to the short-term rental.

This cost reduction is reflected in an increased supply of short-term rentals at any rent in a perfectly competitive market. In figure 2 we demonstrate this effect by flattening the supply curve for short-term rentals in the quantity-price-space. The equilibrium price of short-term rentals decreases, while the quantity of short-term rentals increases.

Figure 2: short-term rental market



Because of the inelastic nature of the housing stock, this increase in short-term rentals can come from a reduction of long-term rentals, or a reduction in non-rented property. The short-term supply of rentals is nearly inelastic so long-term rental supply has to decrease by approximately the increase in short-term rental supply. Long-term rental supply decreases at every price as the cost of short-term rental decreases with the introduction of Airbnb as demonstrated in figure 3. Local residents in long-term rentals will therefore need to pay a higher equilibrium rental price, while the total quantity of long-term rentals is reduced. The marginal propensity of homeowners to reallocate housing from the long- to the short-term rental market will determine the quantity of replaced housing [3].

The consequences of these changes for the housing market (for purchases) are obvious.

The reduction in short-term renting costs increases the value of potential renting opportunities which increases housing demand. The increase in wealth and income of landlords translates into a greater ability to finance further property investment and so demand and so property prices.

The increase in tourists ushered in by Airbnb increases local economic activity and so local incomes and housing demand. These tourists require amenities and services which require land, increasing land demand and so property prices.

Figure 4 demonstrates the increase in demand for housing due to Airbnb. As local housing supply is quite

Figure 3: Long-term rental market

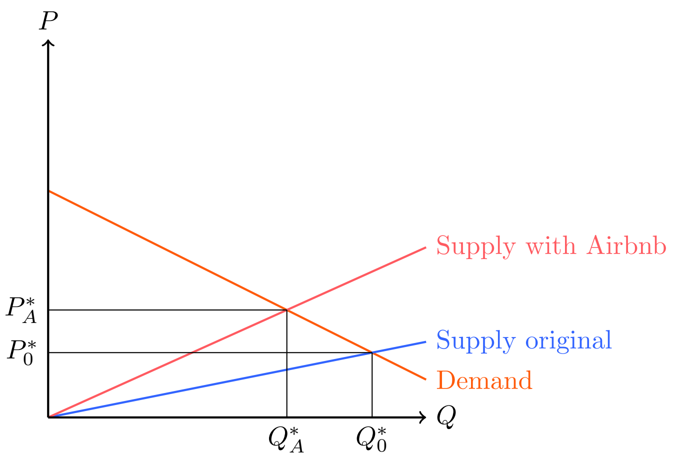
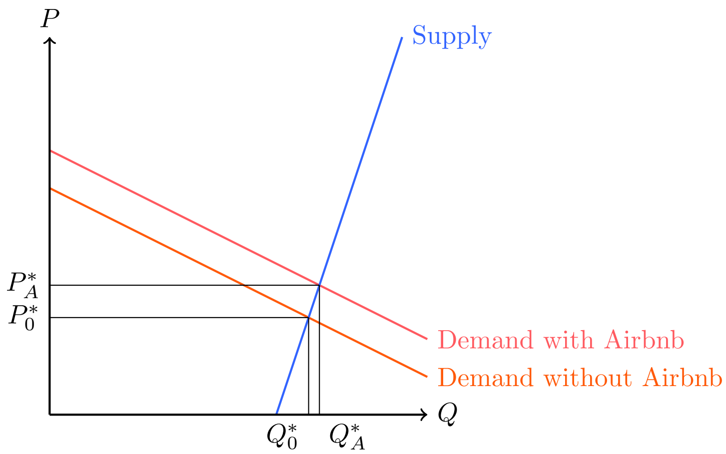


Figure 4: Housing market (for purchase)



inelastic, the presence of Airbnb should result in an increase in house prices according to the channels covered so far.

For this argument to not go through we would have to have strong negative externalities as a result of local Airbnb's. These externalities could include noise and congestion, can be very large and can outweigh Airbnb's other positive price effects, at least locally. As these externalities are highly local, Filippas and Horton argue that while individual owners will oversupply the market, if the decision is left instead to building owners they will internalise the externality and supply the efficient amount of house sharing [5].

4 Data

The analysis was undertaken using microdata on housing transaction covering the period from 2000-2018. This was supplemented by data from http://insideairbnb.com/ which we used in the spatial analysis.

The dataset contains information on sales price, distance to nearest Airbnb listing and the number of Airbnb listings within a 250 metres radius along with housing characteristics to use as control variates. There is known measurement error within the Airbnb variables due to the fact that listing locations are only accurate within 100 metres.

Table 1 contains descriptive statistics for the key independent and dependent variables. We identified a number of outliers, where for example the room size was ≥ 20 or 0, and these were removed.

Figure 7 shows the evolution of house prices using a spatial heat map. To aid visualisation, we have grouped the data into blocks of years. The figure shows the concentration of houses prices by neighbourhood. We have then overlaid the average number of Airbnb listings by neighbourhood, this data is available from 2008 to 2018. The Airbnb data highlights the increasing density of listings over time and the heterogeneity across local areas and presents the possibility to determine local treatment effects.

5 Methodology

Our preferred methodology is Generalised Random Forests, following [2], a nonparametric statistical estimation technique to determine local treatment effects. The local average partial effect of Airbnb presence A_i on housing prices, $\theta(X_i)$, comes closest to a causal effect of Airbnb on house prices. Our local estimating equation is defined $\psi_{\theta(X),\nu(X)}$ contains the local treatment effect $\theta(X_i)$ as well as a nonparametric nuisance $\nu(.)$. It is a function of the observed data, where $O_i = \{P_i, A_i, X_i\}$. P_i represents the observed house price, A_i the Airbnb presence (which we either measure as distance to the closest Airbnb or Airbnb density) and X_i is the set of observed covariates, which have been described in the Data section (excluding x- and y-coordinates).

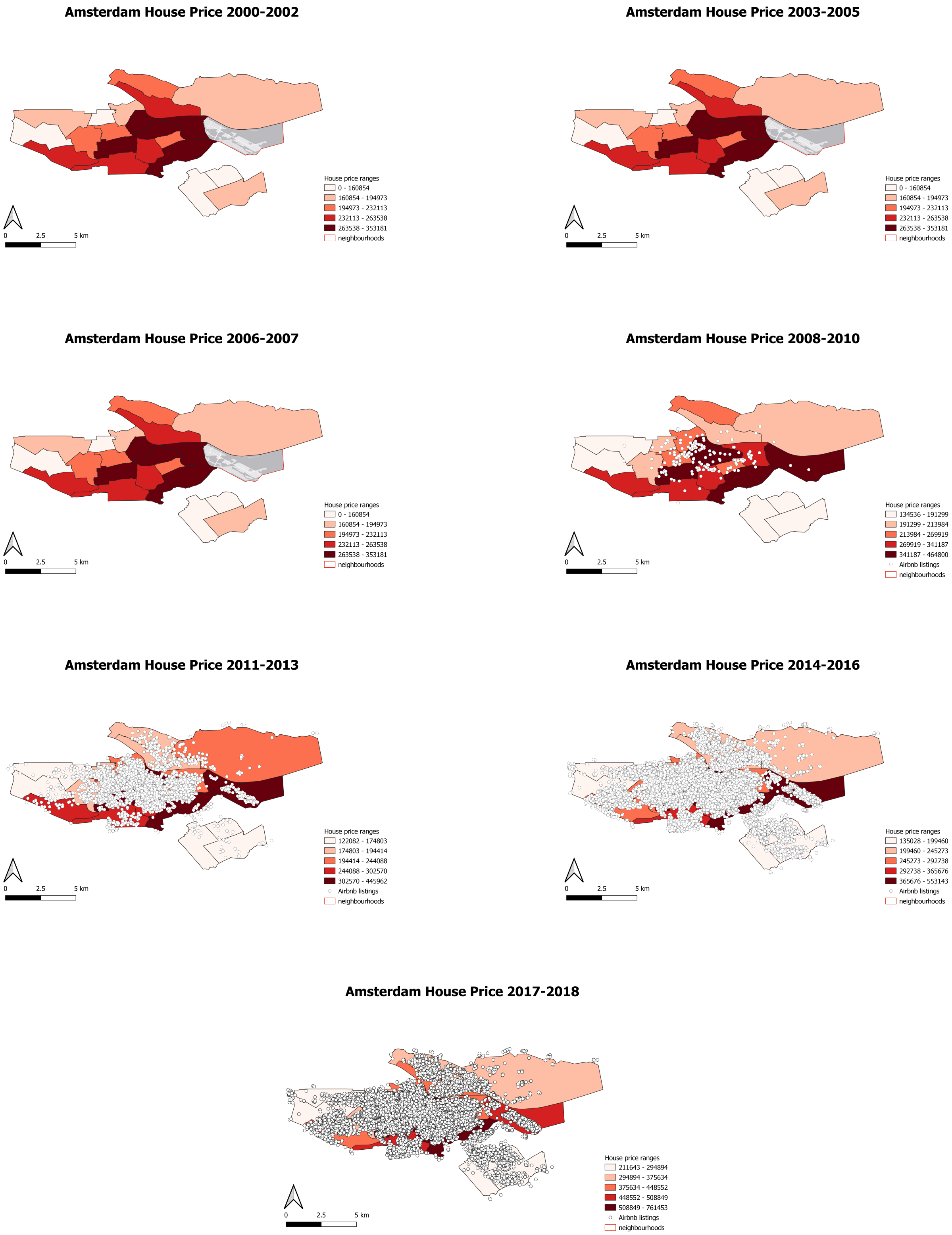


Figure 5: House Price Heat Maps

Table 1: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
price	108,441	301,044	228,108	50,000	173,937	340,000	2,500,000
logprice	108,441	12.447	0.532	10.820	12.066	12.737	14.732
distance	108,441	274.718	882.637	0	0	78.3	8,843
density	108,441	44.000	90.553	0	0	37	685
rd_x	108,441	120,923.900	3,157.516	112,296	118,920	122,991	132,341
rd_y	108,441	486,087.900	2,494.155	477,021	484,880	487,611	493,073
construction_period	108,441	4.195	2.694	1	2	7	9
garden	108,441	0.273	0.446	0	0	1	1
size	108,441	86.667	42.957	25	60	100	1,185
volume	108,441	246.021	142.040	55	162	284	4,740
rooms	108,441	3.248	1.387	0	2	4	103
wtype	108,441	−0.618	1.071	−1	−1	−1	5
parking	108,441	0.104	0.305	0	0	0	1
monumentalstatus	108,441	0.031	0.174	0	0	0	1
buyerpaysorfree	108,441	1.036	0.187	1	1	1	2
quality	108,441	14.395	1.766	2	14	14	18

$$\mathbb{E}[\psi_{\theta(X),\nu(X)}(O_i)|X_i = x] = 0 \tag{1}$$

$$\psi_{\theta(X),\nu(X)}(O_i) = \theta(X_i) - \frac{Cov(P_i, A_i|X_i = x)}{Var(A_i|X_i = x)} \tag{2}$$

Estimation of local moments (instead of global moments) helps us with identification. We estimate the model fully nonparametrically but retain the asymptotic normality of the estimated treatment effects. We allow the effect of Airbnb distance and density to be correlated with unobserved time-specific and area-specific characteristics. The demand for tourism is a typical global confounder in this model. By allowing the random forest algorithm to select any time dummies that matter (in the sense that they predict house price or Airbnb presence), we do not need to include global confounders of house prices, which are the same for all houses at one point in time.
Instead of this flexible approach for local average partial effect estimation, we could have used a simple panel model with location (4 digit zip code) fixed effects α_i, time fixed effects ζ_t to obtain an average treatment effect θ.

$$\mathbb{E}[\psi_{\theta(X),\nu(X)}(O_{it})|X_{it}, A_{it}] = 0 \tag{3}$$

$$\psi_{\theta(X),\nu(X)}(O_{it}) = \theta - \frac{Cov(Y_{it}, A_{it}|X_{it}, \alpha_i, \zeta_t)}{Var(A_{it}|X_{it}, \alpha_i, \zeta_t)} \tag{4}$$

This simpler identification strategy is our benchmark. We estimate the benchmark panel model with the treatments Airbnb density and distance from 2008 onwards, as distance is available only since 2008. The estimate the generalised random forest with treatment distance from 2008 onwards. We also estimate the panel model only with treatment Airbnb density using the data going back to 2008 to see the pre-Airbnb time periods can provide a different perspective on the causal effect of Airbnb (while we continue to condition on time and 4-digit zipcode dummies). A random forest with treatment Airbnb density is run on the same data going back to 2000.

6 Analysis

Our preliminary results point to a nuanced effect of Airbnb on house prices. In all of our tables we condition estimation on observed covariates described in the Data section (excluding x- and y-coordinates). In table 2, the estimated average treatment effect is consistent across specifications. While further distance to an Airbnb seems to increase house prices by 0.1-0.12% for each meter in distance, each additional Airbnb listing in a radius within 250 meters of the transaction appears to decrease house prices by 2.9-3%. These results would allow the interpretation that locally the negative externalities of Airbnbs outweigh the benefits of the simpler rental to tourists, leading to an overall decrease in local housing demand. Nonetheless, as some long-term housing gets replaced by short-term housing, the global demand for housing may still increase significantly. In turn, house prices would increase everywhere.

Table 2: Average treatment effect estimate ˆ for Airbnb distance and density with the panel model and data since 2008

	Dependent variable:			
	logprice			
	Pooled OLS	AreaFE	TimeFE	Both
	(1)	(2)	(3)	(4)
distance	0.0011***	0.0010***	0.0012***	0.0012***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
density	−0.0299***	−0.0291***	−0.0289***	−0.0292***
	(0.0005)	(0.0054)	(0.0052)	(0.0052)
Observations	68,771	68,771	68,771	68,771
R^2	0.7118	0.7398	0.7660	0.7663
Note:				*p<0.1; **p<0.05; ***p<0.01

The results in table 3, for which we used data since 2000, contradict the earlier results for our preferred specifications with area and time fixed effects. While the pooled OLS still shows a negative effect of Airbnb density on price of 2.8% per additional listing in 250 meters, once we account for fixed effects we obtain an estimated 3.4% increase in house prices as a result of an additional listing.

Table 3: Average treatment effect estimate ˆ for Airbnb density with the panel model since 2000

	Dependent variable:			
	logprice			
	Pooled OLS	AreaFE	TimeFE	Both
	(1)	(2)	(3)	(4)
density	−0.028***	0.050***	0.034***	0.034***
	(0.0004)	(0.004)	(0.004)	(0.004)
Observations	108,437	108,437	108,437	108,437
R^2	0.679	0.715	0.732	0.733
Note:				*p<0.1; **p<0.05; ***p<0.01

To address these incoherent results, we turn to random forests. Via k-fold cross validation we chose the optimal minimum node size for prediction of house prices and Airbnb density and distance. We chose 10 as the minimum node size and used over 500 trees in the forest. With the covariates listed in the Data section (including x- and y-coordinates instead of zip code as random forests allows for this additional flexibility), we can predict 88% of variation in log prices, 92.4% of variation in Airbnb density, and 98% of variation in Airbnb density. While such good performance is encouraging, it tells us nothing about the estimated causal effects. The estimated local average partial effects are summarised below.

Just like in table 2, the estimated density average partial effect appears to be mostly negative with a mean of 0.019% decrease in houses prices for an additional listing, while for each additional 100 meter distance from an Airbnb the house price appears to increase by 0.87%. Our generalised random forest estimates in table 4 appear much more realistic compared to the unrealistically large estimates of the panel model.

A useful form to illustrate the estimated treatment effects in our sample is an empirical cumulative distribution plot as in 7. The heterogeneity of the estimated effect shows in this illustration, where estimated effects are on the x-axis. For example, we see that approximately 40% of the density effects are negative at the 10% level of significance, as the estimated confidence interval of the treatment effect with its 5% and 95% percentile lies to the left of 0.

Table 4: Predicted local effect of density and distance on log home price in Amsterdam

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
density	108,437	−0.00019	0.00056	−0.00281	−0.00057	0.00014	0.00641
distance	68,771	0.000025	0.000087	−0.000460	−0.000027	0.000068	0.000514

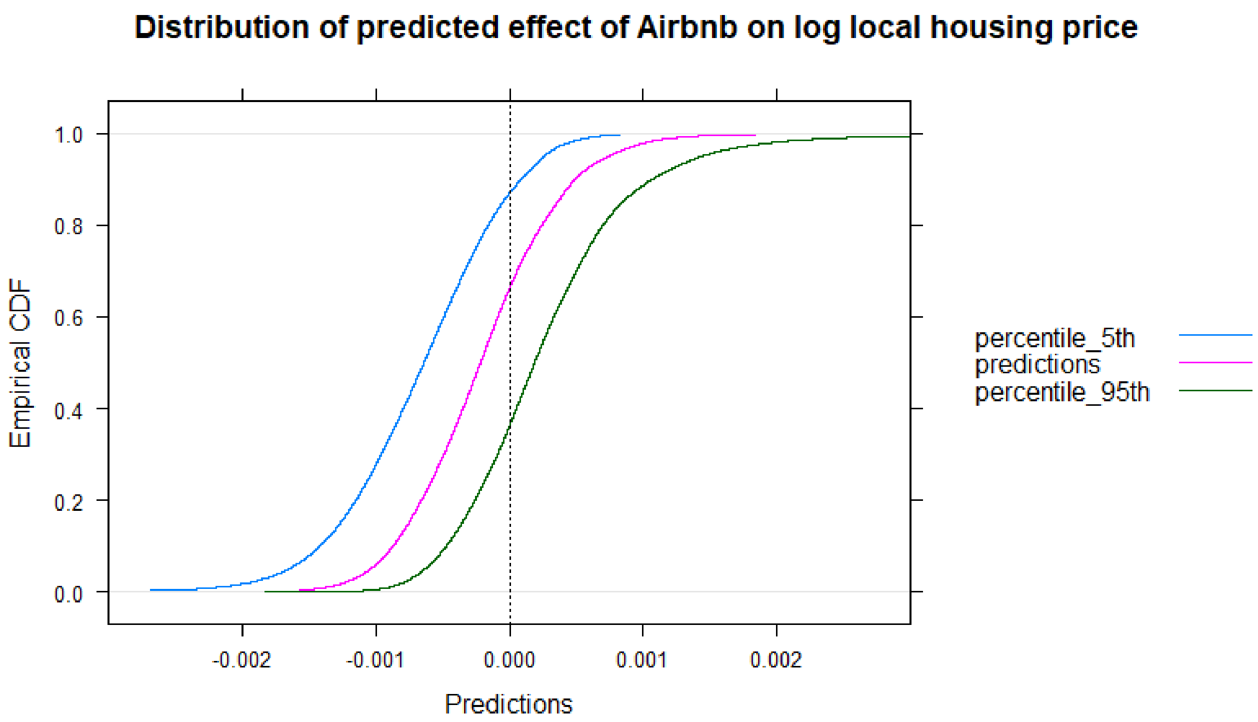


Figure 6: Random forest treatment effect estimate for density

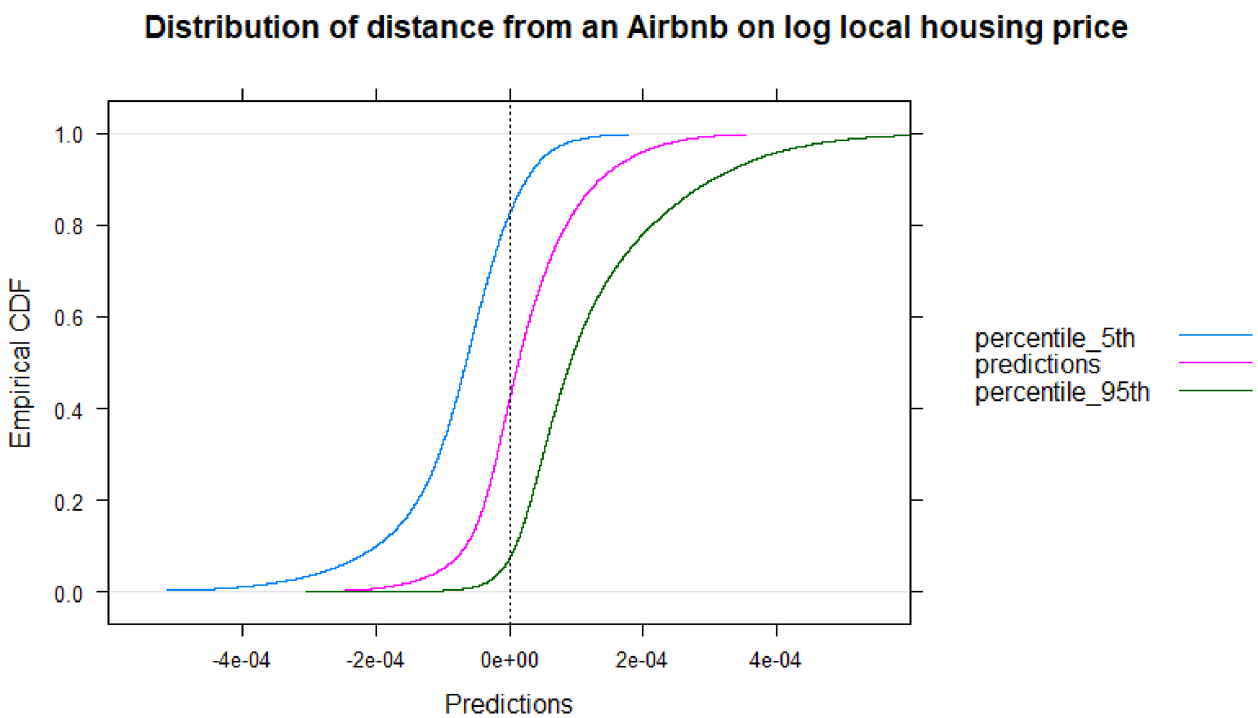


Figure 7: Random Forest treatment effect estimate for distance

7 Conclusion

7.1 Policy Implications

Airbnb rental intuitively has positive and negative externalities, some of which are more concentrated such as noise and some which are more dispersed including spending in the local area. As the presence of Airbnb doesn't appear to uniformly lead to an increase in house prices this suggests that there are indeed negative externalities being imposed on the local area, reducing housing demand in certain areas.

When goods with negative externalities are supplied by individuals they tend to suffer from overconsumption. The negative externalities associated with Airbnb to the local neighbourhood may point toward the need for a local tax on such short-term accommodation. This local tax may be used to help facilitate more housing solutions for those people displaced by the rise in short-term accommodation in affected neighbourhoods however, given the potential positive externalities further cost/benefit analysis would need to be conducted before pursuing such a strategy.

7.2 Further Research

The variables capturing the effect of Airbnb are subject to measurement error which means the local partial effects estimated will be subject to attenuation bias and the true effects may be larger than those presented. It may be possible to identify an instrumental variable for the density of Airbnb within the local area. This would help address the issues associated with measurement error while also addressing the endogeneity challenges we have sought to address using Fixed and Time Effects.
Further use could be made of the spatial data available. We investigated a preliminary high-level analysis using Moran' I: spatial correlation measure. The analysis, given the time constraints, was limited to the relationship between house price and the number of Airbnb listing. The more limited number of house price transactions in the period 2008-10 makes this form of simple analysis difficult and returned insignificant results over this period. However, we found statistically significant results for later years and identified that the house price correlation with first degree Queen neighbour is positive and that the strength of correlation increases over time. Furthermore, that house price and Airbnb listing correlation between first degree Queen neighbours is positive and the strength increases over time. However, the second degree relationship is negative with increasing strength over time. An area for further research would be to include this form of neighbour relationships into the main model we have outlined above
Because of the time constraints we haven't been able to exploit the full benefits of using the Generalised Random Forests approach. An area for further research will be to investigate the variable importance in the forest and better understand the sources of heterogeneity in the treatment effect estimates.

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