Effects of Airbnb on the housing market: Evidence from London.

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October 19, 2021

Abstract

The growth of Airbnb is likely to affect the local housing rental market by reducing the supply of properties. I combine data from Airbnb and Zoopla and examine how the price of individual houses evolves over time, as Airbnb penetrates the market in the area of Greater London. Leveraging the fact that properties with more than three bedrooms are less exposed to Airbnb, I use a difference-in-differences strategy by year and house type. I find that a 10-percent increase in the number of Airbnb properties in a ward increases real rents by 0.1 percent. The effect of Airbnb is highest in one-bedroom properties because these smaller properties are substitutes for hotel rooms, inducing landlords to shift supply from long-let rental market to Airbnb. The impact of Airbnb is heterogeneous, and areas that are more in demand by residents due to better quality schools show a more considerable increase in rents.

JEL Codes: R10, R21, R31, L86, Z30

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I am grateful to James Fenske, Thijs Van Rens and Roland Rathelot for supervision. I also thank Manuel Bagues, Stephen Jarvis as well as seminar participants at the CAGE-AMES (Warwick), Warwick Postgraduate Colloquium in Computer Science, and UN World Cities Day conference for helpful comments.

1 Introduction

The rise of Airbnb, a short-term rental platform has been exponential. The influence of Airbnb on local housing markets, particularly its impact on housing prices, is widely debated in research [1]. A digital platform like Airbnb has faced criticism that it negatively impacts the tenants in the local housing market by increasing the rental prices. However, Airbnb is also associated with the negative externality[2] caused by tourists to the local housing market, like noise and pollution that can reduce the rental prices in the neighborhood. Thus, the effect of Airbnb on rental market prices is ambiguous. The resolution of this ambiguity of the Airbnb effect is essential for local authorities and policymakers who need to balance the renter and landlord's welfare in the local economy. Worldwide, Airbnb has faced strict regulations in major cities like New York, London, Amsterdam, Berlin, Paris, and many more[3]. One reason regulators cite is the increasing cost for living of residents due to platforms like Airbnb. Thus, the estimates of the Airbnb effect on local housing prices can guide the policymakers to take informed decision.

In this paper, I study the effect of Airbnb on housing rentals in the Greater London area by combining two novel datasets. The first dataset is from Zoopla, UK's largest website for rental housing listings. I collected the individual property level data listed on the rental market from 2008 to 2017 on the Zoopla website. From this data, I create a panel of individual-level house rental prices and property characteristics. I combine this data set with Airbnb's property supply data, collected from the Airbnb website. I use the difference-in-differences strategy to identify the effect of Airbnb on housing rental prices. I treat properties with more than three bedrooms as the control group because Airbnb has less than one percent of total properties with more than three bedrooms, while the rental market has a higher proportion (10%) of properties with more than three-bedrooms. Thus, Airbnb should

[1] Horn and Merante (2017); Àngel Garcia-López et al. (2020); Barron et al. (2021); Koster et al. (2021)

[2] Sheppard and Udell (2016); Horton (2015)

[3] San Francisco, Los Angles, Vienna, Tokyo, Hobart (Wegmann and Jiao, 2017; von Briel and Dolnicar, 2020)

not constraint the supply of more than three-bedroom properties in the long-let market. The primary identifying assumption that both treated and control properties located in a small neighborhood should show similar trends in rental prices without Airbnb is validated by examining the parallel trends of rental prices for property types in pre-Airbnb years. Thus, DID estimates the impact of Airbnb on rental properties.

The difference-in-differences also deal with the endogeneity problem where growth in the supply of Airbnb is due to unobserved changes in amenities that attracts tourists within the local housing market itself. Since the long-term housing rental market also responds to neighborhood quality shocks, the endogeneity concerns between Airbnb supply and traditional market rental prices of homes can bias the results severely. This paper uses the DID identification strategy that relies on the individual property panel. Therefore, any ward-level shock that affects the local housing market is controlled by including the ward-year fixed effect in regressions.

Using the DID estimation, I found that a 10% increase in the Airbnb properties in the neighborhood ward increased the real rents of less than equal to three-bedroom properties by 0.1% compared to the control group consisting of more than three-bedroom properties. The growth in the number of Airbnb listings in London was thirty percent in 2017, leading to a large impact on the rental prices of properties. This paper also estimates the heterogeneous impact of Airbnb according to property size. The results show that the rental price in the smaller one-bedroom properties increased to 1.4% from the average effect of 0.1%. This heterogeneous effect on smaller properties is greater in magnitude because one-bedroom properties substitute for hotel rooms, and homeowners supply a higher proportion of properties on Airbnb, thus further reducing the supply of one-bedroom property in the long-term market.

Few studies have estimated the effect of Airbnb on the housing market. Barron et al. (2021) looked at the impact of Airbnb on US cities using shift-share instrument strategy. They found that a 1% increase in Airbnb properties leads to a 0.018% increase in rent.

Koster et al. (2021) studied Airbnb properties in Los Angeles area using local government regulation and found the rent to be down by 5% when Airbnb was banned across the border. Àngel Garcia-López et al. (2020) found a similar effect in Barcelona. My results are closest to Barron et al. (2021), though nearly half in magnitude, which shows the importance of including the ward level time-varying fixed effects. These results thus show that Airbnb can impact the rental prices in London, which has seen an exponential increase in Airbnb listings.

The mechanism through which the home-sharing phenomenon impacts the housing market can be through supply reallocation (Sheppard and Udell, 2016; Zervas et al., 2017). With the entry of Airbnb, now the owner of the property can choose to supply the house between short let market through a platform like Airbnb or supply the property in the traditional long let market. As the demand side market of Airbnb and the long-let rental market caters to different types of people, there are differences in willingness to pay rent for the same property. If renting out property through Airbnb is more profitable, the traditional rental market will face supply constraints as landlords move their property in the short-let market. This reduction in the property supply can cause the rental price to increase in the traditional rental market. Barron et al. (2021); Horn and Merante (2017) show the reallocation of the housing stock from the long term to the short term rental market, making the supply reallocation channel a prominent mechanism of rental price rise in the neighborhood due to Airbnb.

There are few reasons why Airbnb should not impact rent. Airbnb market size is not large enough to impact the traditional housing market. Owners might be very risk-averse and may want a constant income stream through rent rather than a high price through renting out on Airbnb, which comes with the occupancy risk of property like the market of hotel rooms (Coyle and Yeung, 2016; Kim et al., 2017). The negative externality caused by tourism by increasing noise and pollution in the neighborhood also can decrease the rent (Filippas and Horton, 2017). The estimates show that the supply constraint effect dominates the net effect on rental prices. The effect of Airbnb on smaller sized properties is highest, as the one bedroom property is the perfect substitute for hotel rooms. The growth of Airbnb is the primary reason for the supply constraint in this property segment, thus, leading to the maximum increase in price.

I further show the robustness of the difference-in-differences results by testing a placebo effect. Airbnb started its London operations in 2011; therefore, Airbnb's supply from 2011 to 2017 should not impact the rental prices in 2008-2010. I test two placebo strategies - in the first, placebo treatment is given to the pre-Airbnb years (2008-2010) by assigning ward-level supply of Airbnb properties in 2012, 2013, and 2014 to 2008, 2009, and 2010 respectively. In the second strategy, ward-level supply of Airbnb properties in 2014, 2015, and 2016 is assigned to 2008, 2009, and 2010 respectively. Results do not show any impact on the rents.

In the second robustness test, I test whether Airbnb causes more rental price increase in areas with better local amenities. Past research has shown that school quality has a significant impact on housing prices. Airbnb's effect on rental prices is higher in wards where changes in school quality drive positive local demand shocks. I measure positive school quality change as schools converted into academies or new academies opened in the neighborhoods.

I add to the growing literature on Airbnb, which attempts to estimates its effect on the housing market. Barron et al. (2021), Koster et al. (2021), and Àngel Garcia-López et al. (2020) for the USA, Los Angeles, and Barcelona, respectively. Past research has used spatially aggregated data on prices. Spatially aggregated average prices are prone to biases due to changes in the composition of population that is renting and owning the properties. They also produce biased results as neighborhood-level unobserved amenities can impact the entry of Airbnb and long-term rental demand simultaneously. I contribute to the literature by using the individual property panel data in a difference-in-differences methodology to estimate the impact of Airbnb, which is less prone to biases.

I also contribute to the literature by showing that rents of smaller properties increased more due to Airbnb's entry. I use reduced form estimates to document the heterogeneous effect of Airbnb on the housing market based on the size of the property. Smaller properties are in higher demand in the tourist accommodation market thus, homeowners of smaller properties shift more towards the short-term market due to high rental yields. The heterogeneity analysis adds to the recent literature (Calder-Wang, 2021; Almagro and Domınguez-Iino, 2019), which estimates the effect of Airbnb on the welfare of heterogeneous agents.

This study estimates the impact of Airbnb in London, which is a large tourism hub. The local government of London has already regulated Airbnb by creating the licensing mechanism for landlords who want to short-let the property for more than 90 days. The results of this study are important for policymakers because policymakers' welfare function can now take into account the relationship between the presence of Airbnb and rent. Urban local bodies who want to regulate Airbnb can also devise policies based on the property size. This study shows the increase in rent in smaller properties is higher than large properties, so the renters seeking small properties face higher welfare loss than the others.

2 Background

Airbnb is a marketplace that enables people to rent short-term properties. The company does not own any properties but matches property owners or prospective landlords and short-term tenancy seekers and generates revenue from the transaction fees per booking. Airbnb started in 2008 with its first booking in San Francisco as Airbed & Breakfast (Brown, 2016), and now it has over 3,000,000 lodging listings in 65,000 cities across 191 countries. Airbnb is the most prominent home-sharing platform in the UK (Guttentag, 2015). About 1.5 million people reported staying in Airbnb lets in London between 1 September 2015 and 31 August 2016 (Snelling et al., 2016). Levin (2011) shows that this exponential growth is the distinctiveness of internet platforms that can scale start-up-level operations to sizeable industrial-scale operations in a small time frame and lower costs.

2.1 Effects of Airbnb on housing supply

Traditionally the supply-side market has been segmented. Hotel businesses supplied properties to the short-let market, and the traditional housing market supplied to the long-let market. The emergence of peer-to-peer digital market like Airbnb has caused significant changes to this segmented market. Technology lowered the cost of entry for individual owners and provided a flexible supply framework. Properties on Airbnb now compete with traditional avenues like hotels, thus making them a substitute for a hotel room (Einav et al., 2016). According to the data provided by the government's Valuation Office Agency, there are 3.5 million residential homes in London. Total number of properties supplied on Airbnb in London (2017) is around 3.4% of the London's total housing supply. Few studies have empirically shown a negative effect on hotel revenue due to Airbnb's entry (Zervas et al., 2017; Dogru et al., 2019).

The consequences of Airbnb's entry is that property owners who were only supplying in the long-term rental market, now have an additional option of supplying the property in the short-let market. The entry of Airbnb reduces supply in the long-term housing rental market. In short run, if the supply is sufficiently inelastic, the long-term rental price will increase (Barron et al., 2021; Horn and Merante, 2017). UK Housing market is generally known to have an inelastic supply (Hilber and Vermeulen, 2016), and this can make the effect of Airbnb more prominent on the long-term rental market. The magnitude of increase in prices also depends on the land available in the city and the regulations determining the supply (Gyourko and Molloy, 2015).

The quantity of the supply shift of properties from long-term rental to short-term markets and the magnitude of price increase depends on many factors. The homeowner might short-let the spare room and live in the property simultaneously in the genuine home-sharing sense (Quattrone et al., 2016). This would have a negligible effect on the rents as a homeowner does not affect the rental market supply. Without Airbnb, the empty room would not have gone to the long-term rental market. However, this might not be true if the renter can sub-let the property in the short-let market. Subletting provides the existing tenant with the additional income source from unused space and drives up the rents.

The magnitude of Airbnb's effect also depends on the risk averseness of the property owner. Risk-averse landlords might prefer the constant income stream of rent through the long-term rentals rather than the revenue stream subjected to occupancy risk in the short term market. The short term bookings by tourists are inherently risky in terms of assured occupancy. Thus, these risk-averse owners will cause no reallocation of supply, and hence, no effect on prices (Coyle and Yeung, 2016).

Short-let marketplaces like Airbnb can also affect the traditional long-term rental market in ways that can reduce the prices. There can be negative externalities on a neighborhood having a large number of Airbnb rentals. The noise and high tourist inflow can make the neighborhood less desirable to residents (Horton, 2015) and cause downward pressure on rents. However, Airbnb's net inflow of tourists can also increase rents as local businesses may flourish due to tourists. This can lead to higher real estate demand as businesses would want to enter areas with high Airbnb growth. Farronato and Fradkin (2018), and Basuroy et al. (2020) find the positive relationship between Airbnb and restaurant employment, and Jaffe et al. (2017) shows the effect of the positive externality on the neighborhood.

In this paper, I focus on the rental prices, but the price of a property should rise as the expected discounted future rental income rises (Poterba, 1984). The effect of Airbnb should directly reflect on property prices. However, the behavior of the homeowner looking to purchase a property might be different from the renters. The homeowner may value the negative externality due to a high number of Airbnbs in the neighborhood. For example, they might be more sensitive towards noises. If such a case is there, there might be no direct relation between Airbnb growth and increased prices through supply constraints only. Thus I restrict the analysis to short-term rental prices and Airbnb growth in the neighborhood.

The effects of Airbnb on the rental prices in the traditional long-let market can be ambiguous. The property owner can supply in Airbnb market, and by making this choice, the property owner can reduce supply in long let market. This would lead to increase in long-term rents, whereas, the negative externality can make the neighborhood with high Airbnb listings less desirable to residents thus, putting downward pressure on the rents. The net effect of Airbnb is analyzed in this paper, and I found this net effect on the property rentals to be positive.

3 Data

3.1 Airbnb

I am using data from the Airbnb website to infer historical Airbnb supply in the neighborhood. I combine two different sources to achieve the complete data set for the yearr 2008-2017. The first source is the Inside Airbnb[4] initiative, which collects data from the Airbnb website for all the major cities of the world. Researchers have used this data source to show the impact of Airbnb on housing market for eg. Àngel Garcia-López et al. (2020) for Barcelona and Duso et al. (2020) for Berlin. Data for the year 2017 is missing from Inside Airbnb. I use web scraping techniques to get the missing data from the Airbnb website[5]. The data is at the listing or property level and contains information about the property characteristics like the number of bedrooms, various amenities, per day price, address[6], geographic coordinates[7], calendar level availability, host-related information, and property reviews. Airbnb also provides information about the date when the property entered the Airbnb marketplace. I have used this information to construct the history of property activity in the short-let market. This approach has been followed by Zervas et al. (2017), and

[4]Details about the data can be accessed through `http://insideairbnb.com/about.html`.

[5]In December 2017, using automated programs, I web scraped the Airbnb website to get the listing for London city

[6]Depending on the privacy settings, precise address sometime can only be shown to guests with a confirmed reservation

[7]Hosts can choose the privacy setting to show the approximate geocoded location of the listing. This feature was introduced in 2016 where a algorithm generates the random coordinates within 200-300 mts around original address

Barron et al. (2021) to calculate the Airbnb intensity in the neighborhood. Average length of stay of guest is around three days (Haywood et al., 2017), therefore, I classify property listed on Airbnb as a short-term rentals.

I aggregate Airbnb supply using ward boundaries from the Office of National Statistics (ONS). Wards represent the small administrative unit that coincides with the electoral boundaries. Greater London has 633 wards. Ward is chosen as the unit of analysis because they represent the housing market boundaries that have less heterogeneity. The demography of residents and neighborhood amenities have small within ward variations. The spillover across wards is unlikely to cause any significant bias to the results because a recent study by González-Pampillón (2019) finds that spillover effects due to supply shock tend to vanish after nearly 200 meters. The average area of the London ward is two sq. km; therefore, the spillover effect due to properties on the boundary of wards will be small.

3.2 Property rental prices

Data on the traditional long-term rental market is from the online property portal Zoopla. Zoopla attracts 40 million visitors monthly for property search and has the most exhaustive property advertisements. Zoopla has made available historical advertisements of all properties on it's website. I use the data obtained from web scraping techniques using automated programs. The data includes the unique property identification, date of advertisement on the Zoopla portal, rental asking prices, property type (house, flat, bungalow, and maisonette), property size-related information (number of bedrooms, reception, and bathrooms), and address of the property. I use this novel data set to construct the rental supply history of all the properties in London.

Zoopla advertisement data might not represent housing market data because Zoopla has an online presence only. The validity of the data is checked by comparing the data with the representative sample of property market data from the Office of National Statistics

(ONS) and Census data[8]. The report compares the rental price index generated from Zoopla property data and the ONS data. The trend lines shown in Figure A.1 of Appendix 1 are comparable. The report also shows a high correlation between the number of private residential households calculated using the 2011 Census and the number of private rental advertisements in Zoopla, showing that Zoopla property listings are a representative sample of the UK housing market (Appendix 1, Figure A.2). Livingston et al. (2021) compared the estimates of median monthly private rent price from the Valuation Office Agency (footnote) and the Zoopla median prices for all local authorities in England from 2014-2016. The analysis demonstrates the high correlation with R^2 values of 0.97-0.98 showing that Zoopla data is a good proxy of private rental prices.

The posted price of rent might differ from the final transaction price in the housing market. To alleviate this concern, I utilize the transaction-level data from the Zoopla website, which contains the dynamic bargained price history for all the properties. For the unique property listing, I consider the latest asking price to get the accurate rental price under the assumption that the latest asking price is the transaction price itself. Still, for some properties, the latest asking prices can differ from the final agreed-upon prices. However, this might not be a substantial problem as past research (Chapelle and Eyméoud, 2020) show that bargaining is less of an issue for rents, and online posted prices are a good measure of actual rents.

There does exist land registry data that has the property transactions related to purchase and changes in ownership. This data might be slow to adjust to the rental market changes in the short run. The average tenure of a property with the same owner is 12 years and this means that repeated house sales panel data will have fewer transactions in the periods when Airbnb enters the shot-let market.

[8] `https://www.ubdc.ac.uk/media/2050/data-note-260418-analysis-of-zoopla-rental-listings-data.pdf`

3.3 Data on schools and academies

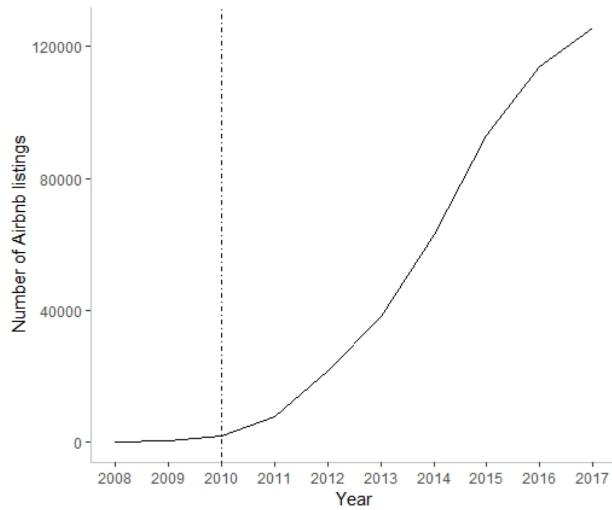
Bertoni et al. (2020) show that families in England have a significant preference for schools that convert to academies. Schools that are 'rebranded' as academies are up to 14% more likely to be ranked as the most preferred choice relative to a baseline probability of picking a first-choice school at random. I use data on school conversion to academies and the opening of new academies to capture the perceived quality of education in the neighborhood. The UK Department of Education provides data on the education institutions. In this data, historical institution type of schools can be identified upto year 2019. I construct a variable identifying the yearly status of the school type indicating whether the school is an academy or not. I use two variables to construct this indicator. The first one has the conversion data of the school, and the second variable is a flag that indicates if the school has been operating as an academy from the day of opening itself. Since the data also provides location of the schools and academies, I finally constructed the ward and year-wise measure of a number of academies in the neighborhood from 2008 to 2017.

3.4 Descriptive statistics

Figure 1 shows the trend of the number of properties supplied through Airbnb marketplace. In the year 2008, Airbnb has no presence in London, but by 2017, the number of total properties listed on Airbnb has grown to 128,000. This significant increase in Airbnb can reallocate the housing supply from the long-term to short-run rentals. The exponential growth of Airbnb is not limited to London, but other cities around the world have encountered a similar trend, e.g. Barcelona (Àngel Garcia-López et al., 2020), USA (Barron et al., 2021), Los Angeles (Koster et al., 2021) , Boston (Horn and Merante, 2017). The London housing market faces supply constraints (Hilber and Vermeulen, 2016) due to planning regulations, and the additional supply constraints due to the growth of Airbnb can impact rental prices.

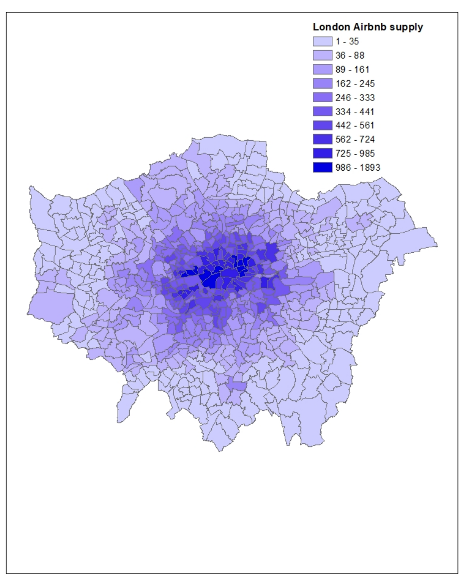
In figure 2, I show the Airbnb listings across the neighborhood level (ward) for 2017. The central part of the city that is popular with the tourists has higher Airbnb listings. Figure 3

Figure 1: Number of Airbnb listings in Greater London area [2008-2017]



shows the average weekly rents (£) in the wards for 2017. There is a high correlation between the number of Airbnb properties and weekly rents, but this may be because local amenities in the wards drive higher rents in long-term rental and Airbnb demand from tourism. So the causal claim that Airbnb is driving up the rents is a challenging research question.

Figure 2: Airbnb supply in wards of Greater London in year 2017



In Table 1, I compare the average weekly rents landlords can receive in the long-let rental market (Zoopla) with the revenue they can expect from their property in the short-let market through Airbnb. I calculate average weekly rental prices and Airbnb prices in the same ward across different property sizes. Table 1 shows that landlords earn over 2.2-2.9 times more on Airbnb when compared to long-term rental market. This calculation assumes that the landlords' choices do not affect prices in both short-term and long-term markets. This differential in short-term and long-term rental prices also represents the inherent risk in renting out through Airbnb due to occupancy risks and can be driven by the selection effect. Still, the large magnitude reflects the high profitability few property owners can achieve by shifting supply from long-term market to short-term market places like Airbnb.

Figure 3: Average weekly rents (£) in wards of Greater London in year 2017

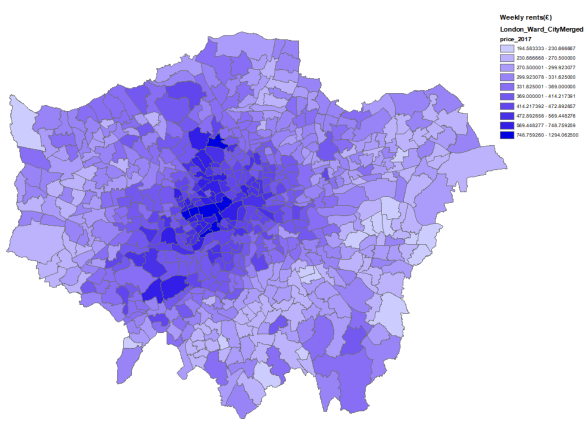


Table 1: Comparison of short-term rental market (Airbnb) and long-term rental market (Zoopla) rents for 2017 (London City)

Number of bedrooms	Rents weekly(£)	Airbnb revenue weekly(£)	Ratio of Airbnb to weekly rents
1	319	714	2.2
2	416	714	2.2
3	571	1596	2.8
3+	736	2130	2.9

4 Empirical strategy

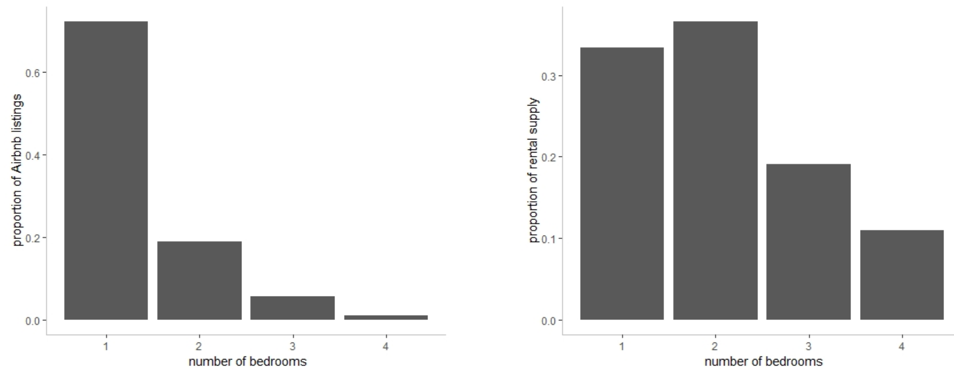
Identifying Airbnb's effect on the housing market is challenging because Airbnb listings are not randomly distributed across the city. Instead, they are concentrated in the areas that are simultaneously attractive to both the residents in the long-let market and the visitors/tourists in the short-let market (Koster et al., 2021; Snelling et al., 2016). So the growth in rents across the neighborhoods are susceptible to endogeneity concerns because the entry of Airbnb in these neighborhoods is itself driven by amenities (Àngel Garcia-López et al., 2020; Barron et al., 2021). Thus, the increase in long-term rents might be driven by the local amenities rather than by the growth of Airbnb properties.

I address this identification challenge in two ways. Firstly, I use the size of the properties to define the control group or the property type whose supply is not impacted by Airbnb's entry. Airbnb generally provides the alternative to hotel rooms (Zervas et al., 2017) and mainly supplies the short-term rental properties that are substitutes to hotel rooms.

Figure (4) compares the composition of properties by the number of bedrooms between the short-let market in Airbnb and the long let market in Zoopla. The comparison in the figure is done using the data for London for the year 2017. The first figure (4a) shows that more than 75 percent of properties listed in Airbnb have only one bedroom supporting the hotel substitutability argument. There are substantial differences between the composition of large-sized properties in Airbnb and the long-term rental market. If Airbnb mainly caters to tourists, it should have a negligible number of properties in the more than three-bedroom segment. The proportion of properties with more than three bedrooms is 10 percent in the long-let rental market, compared to less than 1 percent in Airbnb. Thus, the properties with more than three bedrooms should not encounter any supply constraints due to Airbnb. I use this rationale to use the bigger properties as the control group as Airbnb's growth in the neighborhood should not impact rental prices of more than three-bedroom properties.

The DID methodology also rests on the Stable Unit Treatment Value Assumption (SUTVA). SUTVA requires that the outcome of the unit depends only on the treatment that was as-

Figure 4: Proportion of property types in Airbnb and rental housing market



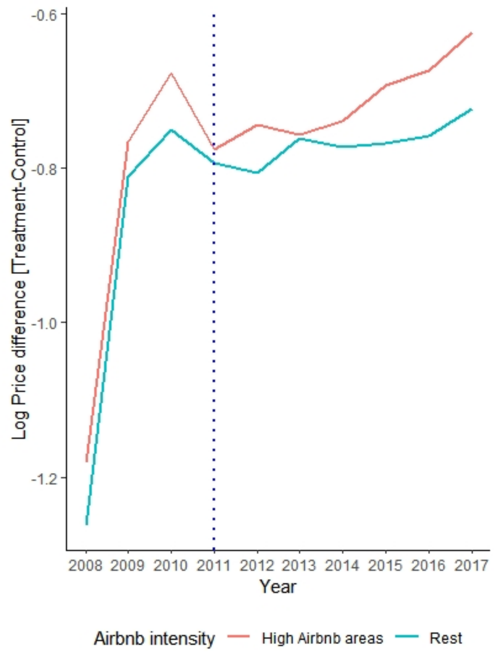
(a) Airbnb (b) Zoopla

signed, not the treatment of others around him. The possible violation might occur when people start substituting into more than three-bedroom properties due to Airbnb's entry as they do not face supply constraints. This assumption is less probable because renters face budget constraints while substituting for large-sized properties. For example, properties with more than three-bedroom have 44% higher rent than the median treated property containing two bedrooms. This sharp increase in rental prices across properties of different sizes makes the SUTVA assumption more plausible.

Secondly, I use the panel data of individual property rental listings. I can control the unobserved neighborhood-level time-varying effect and the property level fixed effect using this novel data. Finally, I employ the differences-in-difference empirical strategy in the individual level panel data of properties. In the differences-in-difference strategy, I take properties with more than three bedrooms as control groups. The remaining properties in the neighborhood are considered as treated units to test if their rental prices are affected by Airbnb, caused by a supply shift in the local housing market.

Figure (5) shows the graphical evidence of this empirical strategy. Each line in the figure tracks the difference in rental growth between Treated (<= 3 bedrooms) and Control (> 3 bedrooms) properties but for different neighborhoods. I compare the difference in rental price growth between neighborhoods with high Airbnb growth and the remaining areas of London.

Figure 5: Evolution of difference in log rent [Treatment-Control] in high Airbnb intensity wards vs the rest. Treated houses are with bedrooms ≤ 3 and control houses are having bedrooms > 3. High Airbnb areas: top 2 deciles of the Airbnb listings in 2017



I define high Airbnb intensity neighborhoods as the wards whose growth in Airbnb listings lie in the top two deciles between 2011 and 2017. Figure (5) show that the gap between both lines has increased. This widening gap shows that areas with a higher Airbnb presence (red line) experienced more considerable growth in the price difference between the treated and control groups than the other areas (blue line). Moreover, the rent gap between the high Airbnb neighborhood and remaining areas of London increased by a larger magnitude post-2013, coinciding with the substantial increase in the Airbnb supply in London as depicted in figure (1).

4.1 Empirical specification

My main empirical specification consists of a difference-in-differences strategy where property rental prices are exposed to supply constraints brought about by the growth of Airbnb properties in the neighborhood. I estimate the regression equation (1) using the property panel data.

$$\ln P^s_{iwt} = \alpha_i + \gamma_{wt} + \eta(lnAirbnb_{wt}) + \beta(\ln Airbnb_{wt} \times D_i) + \epsilon_{iwt} \tag{1}$$

In the the equation (1) P^s_{iwt} measures the rental price of property i in the ward w at year t. $Airbnb_{wt}$ is the number of Airbnb listings in the ward w at year t. I use the logarithm of Airbnb supply and a rental price to estimate the price elasticity of supply (reference?). D_i is the dummy variable indicating whether the property is a treated or a control unit. D_i is equal to one for treated units if the number of bedrooms is less than equal to three whereas, D_i equal to zero for control units having the number of bedrooms greater than three. The variable of interest here is the β as in the empirical strategy, large size properties with the number of bedrooms greater than three are not exposed to Airbnb supply growth and are treated as control units. β in equation 1 shows the differential impact of Airbnb growth on the smaller size properties ($D_i = 1$) when compared to control units in the same neighborhood across time.

I also control for a rich set of fixed effects in DID equation to recover the unbiased estimate of the effect of Airbnb on the rental prices. The γ_{wt} represents the ward-time fixed effect. α_i represents the property level fixed effect. The endogeneity concerns due to unobserved ward level characteristics are alleviated by including the ward-time fixed effects. Shocks specific to the neighborhood (ward), such as urban revival and demographic changes that affect the housing market prices, can be controlled as Àngel Garcia-López et al. (2020) estimated the effect of Airbnb on the housing market of Barcelona. Including the property level fixed effects also controls the property-specific characteristics that might impact rental price. Thus, the inclusion of the fixed-effect helps correct the bias due to unobserved house quality and changes in the composition of house quality in the neighborhood. Housing market price show seasonal patterns within the year

The panel data collated at the property level is an unbalanced panel. Each unit of property is not observed every year because of the data generating process itself. Property is observed in the panel data when it is advertised for rent on the Zoopla website. The fixed-effects model will inconsistently estimate the model parameters if some property units are more likely to be listed in the market in the sample period. Selection of properties in the panel periods must be strictly exogenous, conditional on the individual property characteristics and neighborhood time-variant shocks. This exogeneity condition is most likely to be satisfied in my unbalanced panel, so my results produce consistent estimates (Wooldridge, 2009).

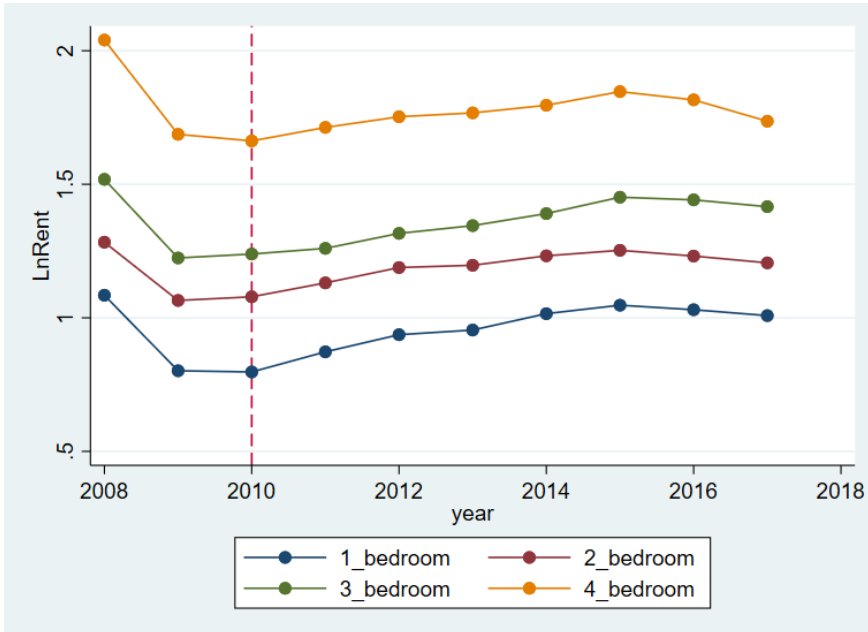
Housing market prices show seasonal patterns within the year. Property prices experience increase in prices and transactions during the spring and summer. In contrast, prices decrease during autumn and winter (Ngai and Tenreyro, 2014). Annual aggregation of data makes this seasonality fluctuation less of a concern. Ward is chosen as the unit of analysis because they represent the housing market boundaries that have less heterogeneity. Wards represent the small administrative unit that coincides with the electoral boundaries. Greater London has 633 wards. The demography of residents and neighborhood amenities have small within ward variations [9]. Wards are ideal as a unit of analysis because of low spillover effect in the housing markets due to boundary effects (González-Pampillón, 2019). The most important identification assumption in the DID equation (1) is that without Airbnb's entry, the growth in rental prices of treated units ($<=$ 3 bedrooms) and control units ($>$ 3 bedrooms) should have similar trends in the neighborhood. Thus, the key underlying assumption of difference-in-differences is the parallel trends assumption.

In the pre-treatment period, when Airbnb is not present, i.e. before 2010, we can test the parallel trends assumption from the data. Figure (6) shows the number of bedroom-wise rental price growth from 2008 to 2017. Though the number of pre-treatment years is only three, all the property types still follow the parallel trend. After Airbnb entered the market in 2010, there is a visible growth in the rental prices of one-bedroom properties in the aggregate data. This paper shows that this visible growth in the rental prices of properties

[9] Profiles of each ward in Greater London. (Authority, 2016)

can be linked partly to Airbnb's exponential growth in London.

Figure 6: Number of bedroom wise log rental price from 2008-2017 in London



4.2 Heterogeneous effects of Airbnb on the property type

Earlier, in figure (4), we compared the composition of the properties by size. Airbnb serves as a substitute for certain types of hotels. Zervas et al. (2017) studies that hotels in the budget and economy segment have the highest negative impact due to Airbnb. These hotels generally have single rooms without any luxury or upscale amenities and are similar to Airbnb properties. Thus, one-bedroom properties are most exposed to Airbnb as demand for small property is highest from tourists. I measure the heterogeneous impact of Airbnb by the number of bedrooms in the property using the regression specification equation (2) below.

$$lnP^s_{iwt} = \alpha_i + \gamma_{wt} + \sum_{r=1}^{3}(lnAirbnb_{wt} \times d_{ir})\beta_r + \epsilon_{iwt} \tag{2}$$

Where d_{ir} is a dummy that indicates if house i has r bedrooms in it and β_r shows the heterogeneous effect of Airbnb on the rental price. I consider the properties having more than three bedrooms as the reference category.

5 Results

In Table (2), I report the results of Airbnb's impact on long-term rents using the empirical specification described in section (4.1). The dependent variable is a logarithm of rental prices of individual properties across the observation years (2008-2017). In column (1), I control for the property fixed effects. The result points that Airbnb supply is associated with the increase in the long-term rents. A 10% increase in Airbnb properties in the wards is associated with a 0.06% increase in real rents of smaller properties as compared to the larger or control properties.

Table 2: Difference-in-differences estimates by year and treated house (property $\leq$ 3 bedrooms)

	ln Rental Price * 100	
	OLS	OLS
	(1)	(2)
LnAirbnb×Treated	0.6340***	0.9310***
	(0.0868)	(0.0928)
House FE	Yes	Yes
Ward*Year FE	No	Yes
Wards cluster	631	631
N	211,498	211,498

Notes. The dependent variable *ln Rental Price* is the logarithm of the rental price of the property listed on the Zoopla website for rental. ln *Airbnb* is lograthim of the number of Airbnb listing in the ward in the year of observation. *Treated* is the dummy equal to 1 when the property has less than equal to three bedroom. Standard errors clustered at the individual property level are reported in the parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

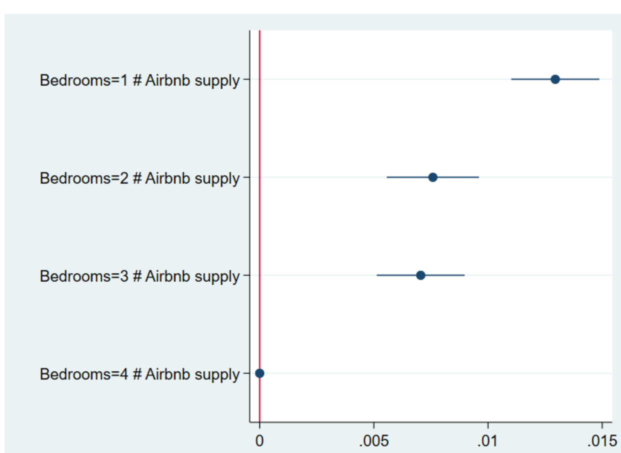
In column (2), I control both for the ward × year fixed effect and property fixed effects. The ward-year fixed effects are incorporated to test if any ward-level time-varying characteristics are driving the results. The coefficient in column (2) is positive and significant, which implies that an increase in Airbnb listing causes the rental price of the treated properties (less than equal to 3 bedrooms) to be more than the control unit (properties larger than the

3 bedrooms). The magnitude of coefficient increased from column 1, showing that Airbnb might be affected by other confounding factors that could affect the results in column 1. This estimate implies that a 10% increase in the Airbnb properties in the wards pushes the real rents of smaller properties by 0.1% as compared to the larger properties.

Figure (7) reports the results of the heterogeneous effect on the rental prices described in the equation (2) of section (4.2). The figure (7) represents the coefficient explaining the effect of the property type by the number of bedrooms. The specification already controls for the individual fixed effects and the ward-time fixed effects. The control group or the properties that have a number of bedrooms greater than three is the reference category. The difference-in-differences coefficient for smaller properties having one bedroom is the largest. Rental prices of one-bedroom increased by 1.4% due to a 10% increase in the Airbnb listings in the neighborhood.

The coefficients of the larger properties are smaller than those of one-bedroom properties and are statistically significant too. The results show that the rental price of properties having only one bedroom increased more than the larger sized properties. In the earlier section (4) using the figure (4), I made this argument through differences in supply constraints. The empirical analysis validated that Airbnb, a substitute for a hotel-like one-bedroom property, increases the rents of similar sized properties in the traditional rental market.

Figure 7: Heterogeneous treatment effect of Airbnb on the property type relative to control group (>3) bedrooms



6 Robustness

The results in the previous section are estimated using the difference-in-differences strategy. In this section, I discuss two potential threats to my identification strategy and provide empirical evidence that the results in the section (5) are robust.

6.1 Time-varying trends between treatment and control units

The validity of the difference-in-differences approach relies on the parallel trends assumption or under the hypothesis that no time-varying differences exist between the treatment and control groups apart from the differential effects causing changes to the treatment groups. The difference-in-differences strategy relies on the parallel trend assumption between treatment and control group. Though the parallel trend assumption is difficult to prove, researchers have shown (Galiani et al., 2005; Bertrand et al., 2004) that visual evidence is one way to access its validity. In the section (4.1) I provide graphical evidence of the common trend assumption, but I can also assess its validity by performing the placebo test. One way is to give fake treatment to some treated units and then access if this produces zero impact. I follow a strategy similar to Schnabl (2012) and add the post-treatment effects in pre-treatment years to test the placebo effect to support the robustness of the results.

Airbnb started its operations in London in 2011. Therefore Airbnb's supply from 2011 to 2017 should not impact the rental prices in 2008-2010. I use two placebo strategies to show that the time-variant Airbnb exposure is causing the increase in the long-term rents. In the first robustness test, placebo treatment is given to the pre-Airbnb years (2008-2010) by assigning ward-level supply of Airbnb properties in 2012, 2013, and 2014 to 2008, 2009, and 2010 respectively. Similarly, in the second test, I give placebo treatment to the pre-Airbnb years (2008-2010) by assigning ward-level supply of Airbnb properties in 2014, 2015, and 2016 to 2008, 2009, and 2010 respectively. I then use this placebo test to estimate the DID equation (1) with placebo treatments.

Table 3: Difference-in-differences (placebo) estimates by year and Treated (less than equal to 3 bedrooms)

	ln Rental Price * 100	
	Placebo 1	Placebo 2
	(1)	(2)
LnAirbnb(placebo)×Treated	0.0987	-1.040
	(0.4060)	(1.2100)
House FE	Yes	Yes
Ward*Year FE	Yes	Yes
N	26,214	26,214

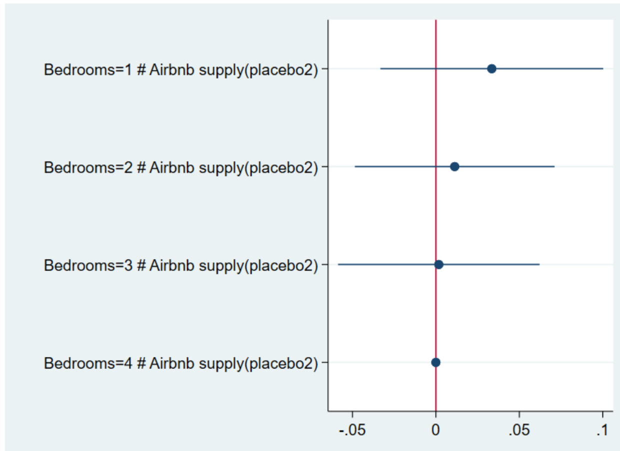
Notes. The dependent variable *ln Rental Price* is the logarithm of the rental price of the property listed on the Zoopla website for rental. ln *Airbnb* is logarithm of the number of Airbnb listing in the ward in the year of observation. *Placebo 1:* The number of airbnb properties in 2012-2014 is re-coded to the same wards in 2008-2010. *Placebo 2:* The number of airbnb properties in 2014-2016 is re-coded to the same wards in 2008-2010. *Treated* is the dummy equal to 1 when the property has less than equal to three bedroom. Standard errors clustered at the individual property level are reported in the parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table (3) presents the results of the placebo treatment. In column (1), the DID coefficients have a positive and small coefficient but large standard errors. Similarly, column (2) has a negative coefficient but has large standard errors. It is plausible that we can't reject any impact of placebo effects for some property type, so I test my placebo strategy using the equation (2) of heterogeneous treatment effect. Figure (8) shows the estimated coefficient of the heterogeneous treatment effects, estimated for placebo treatment strategy where greater than three-bedroom properties are taken as control or reference category. The coefficients indicate that no impact on the rental price due to Airbnb placebo cannot be rejected for all the types of properties.

6.2 Demand of houses in neighborhood and entry of Airbnb

One of the assumptions in the identification strategy is that the neighborhood times year fixed effects can control neighborhood-level trends. The neighborhood-level amenities should not create bias in the results as we can control for these time-varying neighborhood-level fixed effects. This paper adopts the identifying assumption that all property types encounter

Figure 8: Heterogeneous treatment effect of Airbnb placebo treatment on the house type [2008-2010]



the same growth in rental prices due to unobserved neighborhood amenities and uses the difference-in-differences approach. Still, we can test whether segmenting the housing market according to local amenities causes an effect of a different magnitude on the housing market. I do this by segmenting the wards of London into two categories using education quality in the neighborhood as the measure.

Past research has shown that school quality is one of the most influential factors determining property prices (Nguyen-Hoang and Yinger, 2011). The neighborhoods which have high-quality schools face high demand for properties from the population. Another important fact is that school quality does not drive Airbnb's short-let properties' market as tourists' preferences are independent of school quality. Suppose there are two subsets of wards, the first one has higher-quality schools, and the second subset has lower-quality school and there is a similar growth of Airbnb listings in both types of wards. In that case, the neighborhoods providing higher quality education should see higher rental price growth than neighborhoods with fewer quality schools (Collins and Kaplan, 2017; Machin, 2011; Gibbons et al., 2013). This is because the effect of supply constraint is more significant at a location facing demand booms. Hilber and Vermeulen (2016) show this phenomenon in the local housing prices of England where supply constraints due to scarcity of developable land are mainly through regulations.

I use the opening of new academies and the conversion of schools to academies as a variable to measure the increase in the neighborhood's attractiveness due to the perceived increase in education quality. Academies in England are autonomous educational institutions associated with higher academic outcomes (Gibbons et al., 2013). The public school admission process is based on the distance to school from the primary address of the pupil. In the school admission process, parents are generally asked to rank their school preferences in the neighborhood. Bertoni et al. (2020) documented that parents rank academies higher than traditional schools in the admission process and prefer to reside in areas closer to them.

So the presence of academies in the neighborhood (wards) is a sound proxy of the education quality. I divide the wards into two samples to proxy the education quality in the analysis's time frame from 2008 to 2017. The first subset consists of wards with fewer academies, and the second sample includes wards with a higher number of academies (greater than three).

Table 4: Heterogeneous effect of Airbnb: School quality represented by number of Academies in the neighbourhood

	Ln Rental Price * 100		
	Full sample	Academies > 3	Academies <= 3
	OLS	OLS	OLS
	(1)	(2)	(3)
LnAirbnb×Treated	0.931***	1.212***	0.767***
	(0.0928)	(0.1571)	(0.0587)
House FE	Yes	Yes	Yes
Ward*Year FE	Yes	Yes	Yes
Wards cluster	631	83	547
N	211,498	19,562	211,498

Notes. The dependent variable *ln Rental Price* is the logarithm of the rental price of the property listed on the Zoopla website for rental. ln *Airbnb* is lograthim of the number of Airbnb listing in the ward in the year of observation. *Treated* is the dummy equal to 1 when the property has less than equal to three bedroom. Standard errors clustered at the individual property level are reported in the parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

I then run the DID specification (1) on both the samples. Table (4) presents the impact of Airbnb growth on the rents for subsamples based on education quality in the neighborhood. Column (2) shows the magnitude of coefficient for wards with a number of academies larger than three, whereas column (3) shows the remaining wards. The impact of Airbnb on the rents of wards having higher school quality is 80% larger than the remaining wards. The differential effect of Airbnb based on education quality shows that amenities like school quality make an impact that Airbnb amplify in the housing market. The market segmentation based on education quality validates the main result and shows that local amenities do matter in Airbnb's impact on the housing market.

7 Conclusion

This paper studies the effect of Airbnb on the housing market. The exponential growth of short let platforms like Airbnb has disrupted the hotel industry and its impact on the housing markets is increasingly debated. Concerns about the adverse effects on the local housing market have caused the need to investigate the consequences of the Airbnb phenomenon on the traditional housing market.

I identify the effect of Airbnb on long-term rental prices using the difference-in-differences strategy where smaller properties are exposed more to the Airbnb marketplace. Large-sized properties are less affected by the Airbnb phenomenon because Airbnb does not supply more than three-bedroom properties. The identification relies on the rich source of novel property level panel data of long-term rental advertisements. I use one of the largest property listing website's administrative data and merge that data with the Airbnb listings data to estimate the difference-in-differences coefficients.

I focus on the Greater London area and take the control group as the larger properties because Airbnb supplies less than one percent of the total listings in that segment. I control for time-varying ward fixed effects and the individual property fixed effects and find that Airbnb raises property rents. Airbnb constraints supply in the housing market and causes the rental price to increase.

The results show that a 10% increase in Airbnb properties causes a 0.1% increase in rents. The Airbnb impact on the rents of smaller or one-bedroom properties is the largest. This high impact on the one-bedroom properties is in line with the hypothesis that Airbnb is the substitute for hotel rooms, and most of the properties supplied by Airbnb have features of one-bedroom hotel room-like property. I also test the robustness of the results using the placebo test, where I give the placebo treatment of future Airbnb growth to treated units in the pre-Airbnb time. I also test whether Airbnb is more prominent in the areas in demand by the residents. I do this by measuring the changes in education quality as the factor that make the housing market more sensitive to any further constraint in supply due to Airbnb.

A digital market like Airbnb is a new phenomenon, and there is growing research that studies the effect of these non-tradition peer-to-peer markets. The paper adds to the past research in three ways. Firstly, this paper adds London to the growing list of cities that are used as a case study to analyze the effect of Airbnb on the towns and cities worldwide. It adds to the finding that London too faces the rental impact due to Airbnb.

Secondly, I use the novel microdata of individual properties from 2008 to 2017 to build panel data of repeated rents. The magnitude of the Airbnb's impact on the rental market has been debated due to the biases caused by the time-varying neighborhood-level unobserved factors. Using my novel data and applying it to a difference-in-differences strategy, my estimates have less tendency to be biased and produce results that are more accurate and robust.

Thirdly, I show that Airbnb's effect is heterogeneous and depends upon which type of properties face the most supply constraint. Thus, within the ward, not all properties are affected similarly. This paper indicates the importance of property composition as a critical variable that past research has not been able to control.

The results of the paper imply that Airbnb does affect the long-term housing market. This effect has distributional consequences as individuals who seek to rent smaller properties face the most significant rental price increase. The Airbnb effect on rental prices is amplified in the areas which have better amenities like schools. The results of paper are important for policymakers. The local government in major cities is particularly interested in balancing the welfare between the homeowners who typically gain with Airbnb and the renter who loses due to increased rents. This paper shows that renters face an increase in rent in London due to Airbnb, and policymakers should include this in the welfare calculation. If an urban local body or regulator limits the permanent reallocation of supply from the traditional housing market to the Airbnb market, this can increase the renters' welfare.

The paper also shows that the heterogeneous impact on the property type is also an essential factor. Instead of a blanket ban on all property types, regulators can devise property size-specific Airbnb market regulations. For example, London has banned both large and small properties rented out in Airbnb for more than 90 days without permission from the local authorities. The size of the property can be used to reevaluate the welfare calculation in deciding the regulation.

Finally, the limitation of the study is the data of Airbnb is imperfect as it comes from a publicly available Airbnb website that does not have the precise information on the date of exit of the property. This could bias the magnitude of the impact on rental prices. Nevertheless, the fundamental phenomenon that the supply constraint in residential housing due to Airbnb can cause price increases in areas remains valid.

References

Almagro, M. and T. Domınguez-Iino (2019). Location sorting and endogenous amenities: Evidence from amsterdam. *NYU, mimeograph.*

Authority, G. L. (2016). London datastore. *URL: https://data. london. gov. uk 1.*

Barron, K., E. Kung, and D. Proserpio (2021). The effect of home-sharing on house prices and rents: Evidence from airbnb. *Marketing Science 40*(1), 23–47.

Basuroy, S., Y. Kim, and D. Proserpio (2020). Estimating the impact of airbnb on the local economy: Evidence from the restaurant industry. *Available at SSRN 3516983*.

Bertoni, M., S. Gibbons, and O. Silva (2020). School choice during a period of radical school reform. evidence from academy conversion in england. *Economic Policy 35*(104), 739–795.

Bertrand, M., E. Duflo, and S. Mullainathan (2004, 02). How Much Should We Trust Differences-In-Differences Estimates?*. *The Quarterly Journal of Economics 119*(1), 249–275.

Brown, M. (2016). The making of airbnb. *Boston Hospitality Review 4*(1), 1–9.

Calder-Wang, S. (2021). The distributional impact of the sharing economy on the housing market. *Available at SSRN 3908062*.

Chapelle, G. and J.-B. Eyméoud (2020). Can big data increase our knowledge of local rental markets. *Sciences Po Mimio*.

Collins, C. A. and E. K. Kaplan (2017). Capitalization of school quality in housing prices: Evidence from boundary changes in shelby county, tennessee. *American Economic Review 107*(5), 628–32.

Coyle, D. and T. Yeung (2016). Understanding airbnb in fourteen european cities. *The Jean-Jacques Laffont Digital Chair Working Papers 7088*, 1–33.

Dogru, T., M. Mody, and C. Suess (2019). Adding evidence to the debate: Quantifying airbnb's disruptive impact on ten key hotel markets. *Tourism Management 72*, 27–38.

Duso, T., C. Michelsen, M. Schäfer, and K. D. Tran (2020). Airbnb and Rents: Evidence from Berlin. Discussion Papers of DIW Berlin 1890, DIW Berlin, German Institute for Economic Research.

Einav, L., C. Farronato, and J. Levin (2016). Peer-to-peer markets. *Annual Review of Economics 8*, 615–635.

Farronato, C. and A. Fradkin (2018, February). The Welfare Effects of Peer Entry in the Accommodation Market: The Case of Airbnb. NBER Working Papers 24361, National Bureau of Economic Research, Inc.

Filippas, A. and J. J. Horton (2017). The tragedy of your upstairs neighbors: When is the home-sharing externality internalized? *Available at SSRN 2443343*.

Galiani, S., P. Gertler, and E. Schargrodsky (2005). Water for life: The impact of the privatization of water services on child mortality. *Journal of Political Economy 113*(1), 83–120.

Gibbons, S., S. Machin, and O. Silva (2013). Valuing school quality using boundary discontinuities. *Journal of Urban Economics 75*, 15–28.

González-Pampillón, N. (2019, November). Spillover effects from new housing supply. CEP Discussion Papers dp1660, Centre for Economic Performance, LSE.

Guttentag, D. (2015). Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. *Current issues in Tourism 18*(12), 1192–1217.

Haywood, J., P. Mayock, J. Freitag, K. A. Owoo, and B. Fiorilla (2017). Airbnb & hotel performance. Report on the analysis of proprietary data in 13 global markets, STR publication.

Hilber, C. A. and W. Vermeulen (2016). The impact of supply constraints on house prices in england. *The Economic Journal 126*(591), 358–405.

Horn, K. and M. Merante (2017). Is home sharing driving up rents? evidence from airbnb in boston. *Journal of Housing Economics 38*, 14–24.

Horton, J. J. (2015). The tragedy of your upstairs neighbors: Is the airbnb negative externality internalized? *arXiv preprint arXiv:1611.05688*.

Jaffe, S., P. Coles, S. Levitt, and I. Popov (2017). Quality externalities on platforms: The case of airbnb. CESifo working paper 7747.

Kim, J.-H., T. C. Leung, and L. Wagman (2017). Can restricting property use be value enhancing? evidence from short-term rental regulation. *The Journal of Law and Economics 60*(2), 309–334.

Koster, H. R., J. van Ommeren, and N. Volkhausen (2021). Short-term rentals and the housing market: Quasi-experimental evidence from airbnb in los angeles. *Journal of Urban Economics 124*, 103356.

Levin, J. (2011). The economics of internet markets. NBER Working Papers 16852, National Bureau of Economic Research, Inc.

Livingston, M., F. Pannullo, A. W. Bowman, E. M. Scott, and N. Bailey (2021). Exploiting new forms of data to study the private rented sector: Strengths and limitations of a database of rental listings. *Journal of the Royal Statistical Society: Series A (Statistics in Society) 184*(2), 663–682.

Machin, S. (2011). Houses and schools: Valuation of school quality through the housing market. *Labour Economics 18*(6), 723–729.

Ngai, L. R. and S. Tenreyro (2014). Hot and cold seasons in the housing market. *American Economic Review 104*(12), 3991–4026.

Nguyen-Hoang, P. and J. Yinger (2011). The capitalization of school quality into house values: A review. *Journal of Housing Economics 20*(1), 30–48.

Poterba, J. M. (1984). Tax subsidies to owner-occupied housing: An asset-market approach. *The Quarterly Journal of Economics 99*(4), 729–752.

Quattrone, G., D. Proserpio, D. Quercia, L. Capra, and M. Musolesi (2016). Who benefits from the" sharing" economy of airbnb? In *Proceedings of the 25th international conference on world wide web*, pp. 1385–1394.

Schnabl, P. (2012). The international transmission of bank liquidity shocks: Evidence from an emerging market. *The Journal of Finance 67*(3), 897–932.

Sheppard, S. and A. Udell (2016). Do airbnb properties affect house prices? Department of Economics Working Papers 2016-03, Department of Economics, Williams College.

Snelling, C., C. Colebrook, and L. Murphy (2016). Homesharing and london housing market.

von Briel, D. and S. Dolnicar (2020, May). THE EVOLUTION OF AIRBNB REGULATION - An International Longitudinal Investigation 2008-2020. SocArXiv t4nqs, Center for Open Science.

Wegmann, J. and J. Jiao (2017). Taming airbnb: Toward guiding principles for local regulation of urban vacation rentals based on empirical results from five us cities. *Land Use Policy 69*, 494–501.

Wooldridge, J. M. (2009). *Econometrics: Panel Data Methods*, pp. 2769–2792. New York, NY: Springer New York.

Zervas, G., D. Proserpio, and J. W. Byers (2017). The rise of the sharing economy: Estimating the impact of airbnb on the hotel industry. *Journal of Marketing Research 54*(5), 687–705.

Àngel Garcia-López, M., J. Jofre-Monseny, R. Martínez-Mazza, and M. Segú (2020). Do short-term rental platforms affect housing markets? evidence from airbnb in barcelona. *Journal of Urban Economics 119*, 103278.

A Figures

Figure A.1: Rental indices from Zoopla data and the Office of National Statistics (ONS). Sources: (1) Zoopla Property Group PLC 2018, (2) Zoopla Historic Data (UK to 2017)

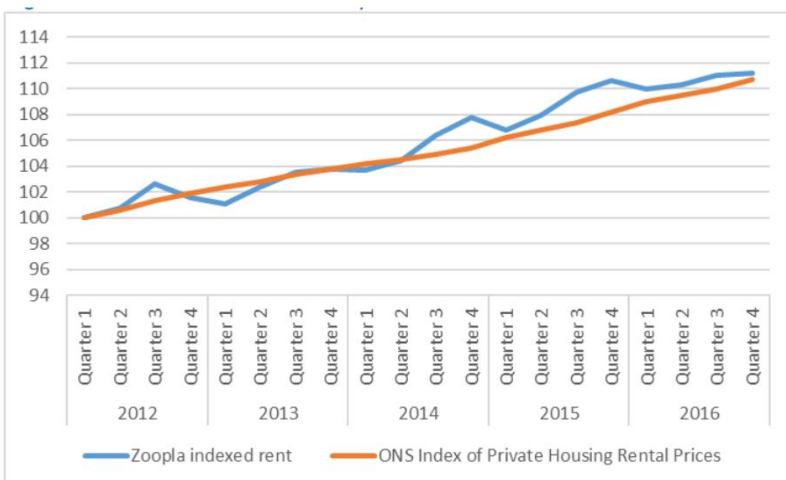


Figure A.2: Scatterplot Private rental households (Census 2011) by number of adverts (2012)