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Article

The Impact of Home Sharing on Residential Real Estate Markets

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Abstract: This paper explores the effects of home-sharing platforms in general and Airbnb in particular on rental rates at a neighbourhood level. Using consumer-facing Airbnb data from ten neighbourhoods located within large metropolitan areas in the U.S. between 2013–2017, as well as rental data from the American online real estate database company, Zillow, this paper examines the relationship between Airbnb penetration and rental rates. The results indicate that the relationship is not as unanimous as once thought. Viewing the relationship at an aggregate level, an approach used by many researchers in the past, hides the complexities of the underlying effects. Instead, Airbnb's impact on rental rates depends on a neighbourhood's individual characteristics. This study also urges policy makers to create tailor-made solutions that help curb the negative impacts associated with the platform whilst still harnessing its economic benefits.

Keywords: sharing economy; time series analysis; random effect panel model; rents

1. Introduction

The sharing, or gig-economy, defined here as a series of platforms that facilitate 'the peer-to-peer-based activity of obtaining, giving, or sharing the access to goods and services' (Hamari et al. 2016, p. 2047) has seen tremendous rates of growth in the past decade and has now become an integral part of our everyday lives. Predictions made by PricewaterhouseCoopers suggest that this economy could grow to generate more than \$335 bn of revenue worldwide by 2025, up from the \$14 bn it created in 2014 (Matzler et al. 2015). At the forefront of this booming economy sits Airbnb, a platform that looks to transform the way in which we utilise our most valuable asset: housing. The platform, which has now become a household name, looks to connect short-term tenants with various types of landlords in an effort to provide a more authentic travel experience to visitors whilst generating economic profits for suppliers.

The success of Airbnb can be seen in numbers: it now advertises over 7 million listings and operates in 191 countries around the world (Airbnb Newsroom 2020). Despite the size of the platform, very little is known about Airbnb and its impact on real estate markets. Existing studies on the effect of Airbnb establishment in the neighbourhood on housing prices are very limited in terms of the geographic areas covered (Zou 2020). Additionally, Airbnb takes great pain in hiding its operations from public view, leading to numerous accusations of tax evasion and an expanding list of third parties taking legal action against the platform. It even creates political tensions and is becoming a hotly debated area in urban development (McNeill 2016). These recent developments make it more important than ever to identify the platform's effects in order to better check its future growth.

Despite the recent criticism, Airbnb, and the sharing economy as a whole, is argued to generate a multitude of economic benefits. It is theorised that the short-term exchanges allow for better resource allocation and utilisation, thereby increasing both the productivity and efficiency of the economy (Jevons 2015). The platforms also lower the barriers to entry in many markets, allowing more users

to list their offerings of goods and services. Furthermore, in the case of Airbnb, the newly generated rental income received by local landlords, as well as the additional spending by tourists, can benefit neighbourhood restaurants and shops, increasing the level of wealth within an area and improving the amenities and services available to local residents.

Nevertheless, many argue that the expansion of Airbnb has brought with it many drawbacks. Firstly, academics theorise that the increase in rental income offered by Airbnb has led to landlords switching to the short-term market in order to profit from tourist demand (Barron et al. 2020). This then decreases the supply of available housing for local residents, which increases rents and exacerbates the already dramatic affordability issue present in many urban centres. Additionally, research has found that a growing proportion of listings on the platform are owned and run by profit-seeking commercial operators. Corporations and wealthy landlords have been able to gain from the expansion of Airbnb at the expense of tenants, thereby exaggerating the divergence between social classes around the world.

The objective of this study is to expand upon the limited existing literature on home-sharing in two main ways. Firstly, the paper will look to isolate the impact that Airbnb has on rents. The analysis will be centred around ten neighbourhoods in some of the largest metropolitan areas in the U.S. and will involve using multiple time-series datasets covering Airbnb listings from 2013 to 2017 and a corresponding set of indexed rental rates in order to test the primary hypothesis that increased Airbnb densities will induce a rise in rental rates at a neighbourhood level. Secondly, the study will use the previously mentioned analysis to investigate viable and effective policy measures that can help curb the negative consequences associated with Airbnb whilst simultaneously harnessing its economic benefits.

The rest of this paper is structured as follows. Section 2 begins by defining what the sharing economy is before analysing its main characteristics and factors of growth. The literature review then focuses on Airbnb's demand and supply side effects and evaluates previous empirical investigations. Section 3 lays out the methodology and datasets used in this analysis, Section 4 presents results and outlines a discussion, Section 5 considers policy implications, and in Section 6, conclusions are made.

2. Literature Review

2.1. The Sharing Economy

Airbnb, and home-sharing platforms more generally, operate within the broader sharing economy. Whilst the sharing economy is a term often used to describe a number of different platforms, it is best defined as a 'set of peer-to-peer online marketplaces that facilitate matching between demanders and suppliers of various goods and services' (Barron et al. 2020, p. 2). Common examples of platforms that operate within the sharing economy include Airbnb, Uber, HomeAway, Lyft, Deliveroo, Fiverr, Doordash, and TaskRabbit. Despite the economy spanning such a vast range of industries, each characterised by different features, the platforms often share common components. On all platforms, the suppliers of products and services look to share excess capacity that might otherwise go underutilised with people that want to use them for a short period of time (Ferreri and Sanyal 2018). Additionally, the platforms do not own any of the assets that they are advertising, but instead facilitate sharing between participants for a fee, often relying on spot-transactions rather than long contracts (Einav et al. 2016; Proserpio and Tellis 2017). With many of the marketplaces being app-based, developers often utilise advancements in technology to improve the matching between buyers and sellers and have implemented reputation and rating systems in order to create a sense of trust on the platforms (Einav et al. 2016). In theory, there are two main segments that operate in the 'pure' peer-to-peer economy. The first are decentralised platforms. These are services that bridge the gap between demanders and suppliers, but leave the searching, matching, and price setting to the participants (Proserpio and Tellis 2017). Examples in this segment include Airbnb, Stashbee, and TaskRabbit. On the other hand, centralised platforms take control and centrally match buyers and sellers, setting prices using tested algorithms. Examples include Uber, Lyft, and Doordash.

The sharing economy, which is projected to generate more than \$335 bn of revenue worldwide by 2025, has seen tremendous growth in recent years and is rapidly changing the ways in which we consume products and services (Proserpio and Tellis 2017). There are numerous reasons as to why this growth has occurred. Firstly, the 2008/09 financial crisis left many without steady incomes or employment opportunities and created a group of people that were unable to pay for assets and services. The sharing economy thus created an opportunity for these groups to turn to alternative platforms that compensated them for providing underused assets. Additionally, the flexibility of these platforms allows users to decide between working on these marketplaces full-time or to use it as a supplement to their regular income. Secondly, a wave of technological advancements, including smartphones, apps, and WiFi has allowed for greater connectivity and has reduced search costs and the time it takes to connect buyers and suppliers. Finally, globalisation has blurred the lines between local and global economies. This has meant that resources that are underutilised in a local economy can now be accessed by users on a global scale (Proserpio and Tellis 2017).

The sharing economy is celebrated by many as an innovation that improves economic efficiencies by reducing the frictions caused by excess capacity whilst also being capable of disrupting established industries (Barron et al. 2020; Proserpio and Tellis 2017). Proponents of these marketplaces applaud the platforms' ability to provide consumers with a better matching and use of resources, lower prices, better offerings, and an overall increase in welfare (Barron et al. 2020). Additionally, the economy's flexibility mentioned previously is argued to foster micro-entrepreneurialism as individuals are able to monetise their assets whilst still contributing to the GDP through their regular occupations (Ferreri and Sanyal 2018). This being said, however, there are many that argue that these platforms' negatives outweigh their benefits. More specifically, recent evidence has shown that the sharing economy may increase societal inequality (Schor 2017) and lower city centre affordability whilst displacing lower income populations to nearby communities (Lee 2016). Furthermore, academics, including Ferreri and Sanyal (2018), contend that the sharing economy has moved away from a forum that allows the exchange of goods and services and towards one where 'venture capital firms come to intervene and influence these processes' (p. 3357).

2.2. Airbnb and Short-Term Rentals

After renting out air mattresses on their apartment floor to attendees of a conference in San Francisco, Brian Chesky and Joe Gebbia founded Airbnb in 2008, which is now recognised as the pioneer of not just the home-sharing industry, but the sharing economy as a whole. Airbnb operates as a peer-to-peer marketplace for short-term rentals, connecting tourists with suppliers of various kinds of accommodations. It is important to note that in most academic literature, short-term rentals (STRs) are defined as 'lettings of up to 30 consecutive days' (Koster et al. 2018, p. 8). The website allows its users to advertise three different types of listings: a shared room, a private room, or an entire unit. Local authorities and academics often distinguish between two types of short-term rentals. 'Home-sharing', which includes Airbnb's shared and private room listings, is usually defined as a STR where at least one of the primary residents lives on-site during the tourists' stay. 'Vacation rentals', on the other hand, are where the tourist occupies the entirety of the letting (Koster et al. 2018). Seeing as Airbnb operates in both segments, the platform has essentially created a new category of rental housing which blur the lines between traditional rentals and hotel accommodation.

Furthermore, the platform's business model is simple: hosts list their offerings on the marketplace for a price set by themselves, while Airbnb takes a commission of anywhere from 7% to 18% per booking (Wachsmuth and Weisler 2018). This being said, Airbnb takes great pains in order to hide its operations from public view and has been claimed to bypass regulations and 'undermine policies aimed at protecting the supply of affordable housing' (Wachsmuth and Weisler 2018, p. 5). It is often argued that Airbnb has moved away from a sharing platform to one that incentivises large scale operators to accumulate additional properties in search for profit. For example, in Los Angeles, researchers found that these large-scale property developers earn huge revenues; just 6% of hosts list more than one

property and yet they earn 35% of all Airbnb revenue (Lee 2016). DiNatale et al. (2018) surveyed the Airbnb markets in 237 cities in Oregon, USA. They found that nearly 40% of Airbnbs are whole homes that are rented more than 30 days in a year, which potentially has significant impacts on long-term rental supply in those cities.

Airbnb's rapid growing in many cities raised serious concerns in a wide range of areas such as anti-social behaviour (noise, disruption), public health, safety, fire risk, availability and affordability of permanent rental housing, impacts on local services and tax revenue, and impacts on the tourism industry (Gurran and Phibbs 2017; Gurran et al. 2018). Although Airbnb position itself as the poster child of sharing economy by providing temporary supplies to the tourism sector, evidence is found that Airbnb actually removes residential units from housing market permanently (Crommelin et al. 2018; Schäfer and Braun 2016; Vinogradov et al. 2020). There are growing concerns about Airbnb's role in the financialization of housing (Cocola-Gant and Gago forthcoming; Grisdale 2019), displacement (Cocola-Gant and Gago forthcoming; Yrigoy 2019), and tourism-led gentrification (Robertson et al. 2020; Wachsmuth and Weisler 2018).

Despite these criticism and concerns, Airbnb has seen tremendous rates of growth since its incubation in 2008. Airbnb now has over seven million properties on its platform, listed by over two million hosts in 81,000 cities and 191 countries worldwide, more than twice as many as its closest competitor, HomeAway (Airbnb Newsroom 2020; Barron et al. 2020; Wachsmuth and Weisler 2018). Additionally, Airbnb has provided accommodation to over 500 million guests, allowing it to gain a monopolistic position in many of the cities in which it operates (Airbnb Newsroom 2020; Ferreri and Sanyal 2018). Despite attempts at regulation in order to protect local markets and curb Airbnb's growth (Cassell and Deutsch forthcoming), these numbers are still expected to rise. While Airbnb has yet to have its IPO, the platform's market penetration and profitability figures has resulted in a valuation of over \$31 bn, making it larger than some of the World's leading accommodation chains including the Marriot and Hilton groups (Proserpio and Tellis 2017).

2.3. The Effects of Airbnb on Rental Real Estate Markets

It is often theorised that Airbnb has two competing effects on local rental property markets. On the one hand, the extra rental income earned by local residents is argued to enable some citizens to continue living in 'booming' housing markets. On the other hand, the high revenues earned from short-term rentals mean that property owners of all types have an incentive to shift their supply from the long-term market to the tourist market, which increases rents for long-term tenants. In support of the latter argument, recent research by academics in both Europe and the USA have found that Airbnb often distorts rental markets through either a supply effect or a demand shift.

Perhaps the leading theory on Airbnb's effect on residential markets is that the expansion of the platform has caused a supply shift from the long-term to the short-term rental market, decreasing total supply in the long-term and increasing rents for local tenants. Academics suggest that the market for long and short-term rentals is segmented on both the demand and supply side. This segmentation is argued to exist for many reasons. On the demand side, tenants will have different needs depending on the length of their stay: the potential tenants of short-term accommodation are usually tourists, business travellers, and other visitors who may only be looking for a bed and bathroom. Local residents seeking a more comprehensive dwelling, on the other hand, create the demand for long-term accommodation (Barron et al. 2020). On the supply side, there may be legal restrictions which do not allow for the transfer of accommodations from different term structures; additionally, landlords may prefer one length of letting to another or may be unable to switch due to contractual obligations.

This segmentation has created a term structure of rents, with the rents coming from short-term accommodation typically being much higher than the rents coming from long-term lettings. The gap between the two term structures is often referred to as the 'home-sharing premium'. The expansion of home-sharing platforms like Airbnb have reduced the frictions between the two segments and has allowed for the transfer of accommodation from the long-term to the short (Horn and Merante 2017).

Furthermore, seeing as the supply of housing is fixed or highly inelastic in the short-run, this transition results in a decreased supply of long-term rental properties and puts tourists in direct competition with local renters, raising prices for all long-term accommodations (Lee 2016). This issue is exacerbated by the fact that, in many cities, both private and public developers are already unable to build enough new homes for their residents.

There is substantial evidence that a supply side factor has contributed to the rising rental prices in many cities. Focusing on U.S. metropolitan areas, Barron et al. (2020) engaged in regression analysis to discover a causal relationship between Airbnb penetration and rental rates. More specifically, they found that, on average, a 1% increase in Airbnb listings led to a 0.018% increase in indexed rental rates. Consistent with the supply side theory, they found that higher rates of Airbnb listings resulted in fewer dwellings being vacant and available for rent. This, together with the fact that there was no effect on the total housing supply, led to their conclusion that Airbnb affects rental real estate markets through a supply side effect (Barron et al. 2020).

In a research journal published at a similar time, Horn and Merante (2017) focused more closely on Boston, a single city in the U.S. Their initial analysis had found that in Boston, while 82% of the hosts had only one simultaneous listing on Airbnb, the 18% of hosts that did have multiple listings represented nearly 50% of all dwellings. This suggests that Airbnb may have evolved into an operation that is dominated by profit-seeking commercial operators. Their main piece of analysis involved an examination of whether Airbnb presence is associated with higher rents in the following time period. The researchers found that a one standard deviation increase in Airbnb listings relative to the total units of housing within a census tract increased listed asking rents by 0.4% and decreased the number of rental units offered by 5.9% (Horn and Merante 2017). Once again, these results support the supply side theory mentioned previously.

Outside of the U.S., few studies have estimated the effects of Airbnb on the supply of rental housing. However, a working paper published by Garcia-López et al. in 2019 used similar processes in order to analyse markets in Barcelona. Having access to individual-level data on transactions of second hand apartments sold in the city, as well as a summary of all advertised rental listings, they were able to conclude that rent levels were higher in areas with more Airbnb activity; specifically, their results suggested that, on average, an increase of 54 active listings in a neighbourhood increased rents by 1.9% (Garcia-López et al. 2019).

Another prominent theory argues that Airbnb affects rents by creating a rent gap in the markets in which it operates, which then leads to gentrification. Neil Smith's original rent gap model, which was proposed to explain the gentrification trends occurring in American inner-cities, is underpinned by two key theoretical concepts: 'actual' and 'potential' economic returns, or ground rents (Smith 1979). Actual ground rent refers to the rent currently received by the landlord, given the present use of land whilst potential ground rents are the 'amount that could be capitalised under the land's highest and best use' (Smith 1979, p. 543). Smith (1979) argues that rent gaps are created when there is a divergence between actual and potential ground rents, often resulting in real estate investment flowing in. This increase in investment will likely 'drive up rents, attract more affluent residents and displace the neighbourhood's existing residents' to nearby communities (Wachsmuth and Weisler 2018, p. 7). Airbnb, and the home-sharing premium associated with the platform, is argued to create a new highest and best use of residential properties, resulting in the creation of a new potential ground rent.

This technologically driven rent gap, however, is different to those proposed by Smith (1979). In the case of Airbnb, there is no dramatic decrease in actual ground rents due to capital depreciation prior to the gap emerging. Rather, the expansion of Airbnb acts as an exogenous shock to the market, instantaneously creating a divergence between actual and potential ground rents. Additionally, in the standard rent gap theory, in order for gentrification to occur, the gap must become wide enough to justify the cost of renovations or new construction; however, with the little to no cost involved with listing a dwelling on Airbnb, the gap does not have to pass a certain threshold before gentrification

occurs. In practice, however, it is difficult to prove that the technologically driven rent gap exists due to the difficulty in measuring the highly theoretical concepts of actual and potential ground rents.

Focusing on New York City, researchers Wachsmuth and Weisler (2018) find that Airbnb has created new potential revenue streams for landlords and has had geographically uneven effects. The paper is able to find clear evidence of a rent gap by investigating empirical indicators of actual and potential ground rents. More specifically, the researchers discover that some areas offer Airbnb hosts revenues of 200–300% higher than from median rents. Furthermore, the platform's greatest disruption has been on affluent neighbourhoods that have already been gentrified, leading to wealthy landowners capturing many of Airbnb's economic benefits at the expense of local residents.

Additionally, after noticing the lack of empirical studies that address the rent gap in the context of Europe, Yrigoy (2019) looked to quantify the gap between rental income vis-à-vis tourist rentals in the Old Quarter of Palma de Mallorca. By estimating a yearly potential revenue from Airbnb listings, he found that the income generated by tourist rentals more than tripled that earned by dwellings rented to local residents despite there being far fewer units available. Once again, this is clear evidence of the rent gap. The paper also argues that the rent gap has contributed to tourism-gentrification, whereby the capital flows toward real estate, as well as a boost in the urban tourism market, pushes out local residents in favour of more affluent newcomers (Yrigoy 2019). The researcher concludes that, despite the gradual decrease in revenues generated from individual tourist lettings, landlords will continue switching from the long to the short-term market until rents equalise and the rent gap disappears.

The majority of the literature cited here offers an over-simplistic view of the dynamics through which Airbnb operates. More specifically, the papers often rely on analysing the relationship between home-sharing and rental rates at an aggregate scale and fail to examine the many discrepancies present between specific rental markets. This paper looks to supplement the literature by examining Airbnb's effects at a neighbourhood, or zip code level.

3. Data and Methods

This paper makes use of several datasets which cover Airbnb use in ten neighbourhoods within large cities in the United States. Additionally, data has been obtained on the rental rates and numerous demographic characteristics in said neighbourhoods.

3.1. Selection of Neighbourhoods

Unlike many previous studies, which have looked to analyse the effects of Airbnb on an aggregate scale, we have chosen to develop a framework that isolates the platform's effects on individual neighbourhoods. As will be described in detail later, whilst the rental and demographic data are both captured at a zip code level, the Airbnb data we have collected is categorised by neighbourhood. Therefore, in order for any analysis to be meaningful, we have had to handpick neighbourhoods that are serviced by a single zip code. In doing so, we have been able to compare the different variables in a geographically reliable manner. The ten neighbourhoods chosen, along with several of the neighbourhoods' key characteristics, can be seen in Table 1.

The ten areas chosen ranges from sparsely populated neighbourhoods such as Northwest Portland, to highly populated ones such as Logan Square, Chicago. Additionally, they cover a great variety of population densities, with just 1718 people per km² in La Jolla, San Diego compared to the 20,887 people per km² in North Beach, San Francisco. Finally, whilst all of the neighbourhoods chosen have a median household income above the national average of \$59,039, the sample still allows us to analyse how Airbnb's effect on a neighbourhood changes with differing levels of wealth.

3.2. Dependent Variables

In line with studies done in the U.S. by Barron et al. (2020) as well as Horn and Merante (2017), we chose to utilise the Zillow Rent Index (ZRI) as a proxy for long-term rental rates in the ten cities analysed. Founded in 2006, Zillow is an American online real estate database company that creates a

monthly dollar-valued index that is intended to capture the typical market rent for different geographic granularities across the U.S. (Zillow). The ZRI relies upon both real listings as well as the company's own Rent Zestimates, or estimated rental prices. More specifically, Zillow reports the mean of the middle quintile of all listings and Zestimates in a given rental market. Additionally, the company produces numerous ZRIs that focus on different segments of the market (single-family, condo, multi-family, and all homes); this paper focuses on the 'all-homes' index, as it is most representative of the listings on the Airbnb website. The final result is several time-series datasets of rental indices at a zip code-month level for every month for which there is Airbnb data available, covering the time period between 2013 and 2017.

3.3. Independent Variables

In order to control for demographic changes that can affect the rents in a given neighbourhood without impacting the Airbnb metrics described below, the paper looks to include several key zip code level time-varying characteristics. The paper includes estimates of a zip code's unemployment rate, median household salary, percentage of workforce with a bachelor's degree or higher, poverty level, total housing supply, and vacant housing supply. In line with previous studies, all of these estimates are collected from the American Community Survey (ACS). The ACS is conducted by the U.S. Census Bureau on a yearly basis and is regarded as the most credible and up-to-date resource available. Furthermore, in order to match the other datasets used, we have had to linearly interpolate the yearly observations to create monthly estimates of the time-varying characteristics.

As mentioned previously, Airbnb's revenue figures and operations are not accessible to the public. Therefore, in order to analyse Airbnb's penetration, this paper relies on consumer-facing information collected by Tom Slee, a leading academic in the field. Slee used an algorithm that takes web scrapes directly from the Airbnb website at monthly intervals from 2013 to 2017 in several large cities in the US. A web scrape is essentially an instantaneous snapshot of all of the dwellings listed on the Airbnb website in a given neighbourhood at a given point in time. Several key pieces of information are derived from these snapshots including, but not limited to: the unit and host ID, the type of listing, the dwelling's neighbourhood, the price per night, and the number of reviews. This method results in the closest estimate of the true number of listings on the marketplace, with Slee arguing that the algorithm 'gives a count of Airbnb listings in a city that is usually within 10% of the correct number' (Slee). The final datasets include over 260,000 listings in the ten neighbourhoods mentioned previously, making it one of the most comprehensive studies recorded to date.

Consistent with research conducted by [Horn and Merante \(2017\)](#), this paper utilises Airbnb density measures as a proxy for Airbnb penetration. More specifically, two density measures are used for robustness sake. The first variable measures Airbnb density as a proportion of the total supply of housing. It is measured by dividing the number of active listings in a neighbourhood, derived from the web scrapes mentioned previously, by the number of total housing units in the given zip code. The second density metric measures Airbnb density with regard to the number of vacant units in the market. It divides the total number of active listings by the number of vacant dwellings in the neighbourhood. By using a density metric as opposed to the absolute number of listings, the paper is better able to control for changes in population and housing construction. Estimates of both the vacant and total supply of housing in these neighbourhoods are taken from the American Community Survey, as described previously. Tables 2 and 3, below, provide a summary of all of the variables' descriptive statistics as well as their corresponding definitions and sources. Figure 1 shows the correlation coefficients among the three key variables: ZRI (Zillow Index), Airbnb1 (Airbnb Density 1), and Airbnb2 (Airbnb Density 2). A positive relationship is identified in most of the cities.

Table 1. Neighbourhood characteristics.

Neighbourhood	City Population	City Size (km ²)	City Population Density per km ²	Neighbourhood Population	Neighbourhood Size (km ²)	Neighbourhood Population Density per km ²	Neighbourhood Median Family Income (\$)
Fenway, Boston	695,926	232.1	2998.3886	25,619	3.212	7976.027397	76,643
Logan Square, Chicago	2,705,988	606.1	4464.59	87,509	8.37	10,455.07766	68,223
Venice, LA	10,105,518	1302	7761.5346	27,525	8	3440.625	115,967
Greenpoint, NYC	8,398,748	783.8	10,715.422	36,492	7.133	5115.939997	78,287
Rittenhouse Square, Philadelphia	1,584,138	367	4316.4523	24,219	4.43	5467.042889	138,611
Northwest, Portland	652,573	375.5	1737.8775	17,585	3.44	5111.918605	118,404
La Jolla, San Diego	3,343,364	964.5	3466.422	39,742	23.13	1718.20147	107,094
North Beach, San Francisco	883,305	121.4	7275.9885	26,527	1.27	20,887.40157	66,422
Broadway, Seattle	744,949	217	3432.9447	25,448	4.248	5990.583804	83,403
Georgetown, Washington DC	633,427	177	3578.6836	27,562	3.035	9081.383855	220,000

Table 2. Identification and definition of variables.

Variable Type	Variables	Description	Source
Dependent Variable	ZRI	A monthly dollar-valued index of the typical market rent at the neighbourhood level	Zillow
Independent Variables	Airbnb1	Airbnb density as a proportion of the total stock of housing at the neighbourhood level	Tom Slee/ACS
	Airbnb2	Airbnb density as a proportion of the vacant stock of housing at the neighbourhood level	Tom Slee/ACS
	Number of listings in City	Total number of Airbnb listings at the city-wide level	ACS
	Total housing stock	Estimated number of housing units at the neighbourhood level	ACS
	Total vacant housing	Estimated number of vacant housing units at the neighbourhood level	ACS
	Unemployment rate	The number of people unemployed as a percentage of all people aged 16–64 at the neighbourhood level	ACS
	Median salary	The median family income in USD at the neighbourhood level	ACS
	% of workforce with bachelors or higher	The number of people with a bachelor's degree or higher as a percentage of all people aged 25–64 at the neighbourhood level	ACS
	Poverty level	The number of people under the national poverty line as a percentage of all people aged 16–64 at the neighbourhood level	ACS

Note: Data sources: Zillow: <https://www.zillow.com>. Tom Slee: <http://tomslee.net>. ACS: American Community Survey, <https://www.census.gov/programs-surveys/acs>.

Table 3. Descriptive statistics.

Variables	Mean	Standard Deviation	Minimum	Maximum
ZRI	3476	1368	1800	6030
Airbnb1	3.56%	3.27%	0.27%	14.99%
Airbnb2	37.67%	32.15%	2.48%	128.89%
Number of listings in City	10,801	10,478	1275	41,245
Total housing stock	19,515	11,055	8360	72,330
Total vacant housing	2049	1121	648	6054
Unemployment rate	6.14%	2.76%	2.11%	14.50%
Median salary (\$)	100,676	46,815	51,675	227,424
% of workforce with bachelor's or higher	65.41%	15.58%	31.42%	88.05%
Poverty level	13.25%	7.91%	4.17%	37.80%

**Figure 1.** Correlation between property price index and Airbnb density in ten American cities.

3.4. Models

This paper aims to estimate Airbnb's impact on rents at a neighbourhood level. The hypothesis is that higher Airbnb densities in a neighbourhood will increase the rent level due to landlords shifting away from supplying the long-term market in favour of the newly available, and more profitable, short-term market. We tested the existence of a long-term relationship between Airbnb densities and rents by using panel data regression method, and the short-term dynamics between Airbnb densities and rents by using first differenced linear regression models created with a stepwise selection procedure.

Our monthly data cover ten American cities over the period between 2013 and 2017¹. This gave us an unbalanced panel data set of 254 observations due to some missing values at the beginning of the sampling period. We performed a Hausman test to check whether a fixed effect or a random effect panel model should be estimated. The test results suggest a random effect model. We estimated the following two models accordingly

¹ Our sample period stops at 2017 because the key Airbnb density information is unavailable after 2017. Specifically, Tom Slee stopped releasing such data at his website after 2017.

$$Y_{i,t} = \alpha + \beta_1 \text{Airbnb1}_{i,t} + \sum_{j=1}^k \alpha_j x_{j,i,t} + \tau_i + \theta_{i,t} \quad (1)$$

$$Y_{i,t} = \alpha + \beta_1 \text{Airbnb2}_{i,t} + \sum_{j=1}^k \alpha_j x_{j,i,t} + \tau_i + \theta_{i,t}, \quad (2)$$

where $Y_{i,t}$ is the ZRI in neighbourhood i at month t ; $\text{Airbnb1}_{i,t}$ is the measure of Airbnb density as a proportion of the total stock of housing in the same neighbourhood, i , at month t ; $\text{Airbnb2}_{i,t}$ is the measure of Airbnb density as a proportion of the vacant stock of housing; $x_{j,i,t}$ is the j th neighbourhood-level characteristics in neighbourhood i at month t . τ_i and $\theta_{i,t}$ are the within-entity and between-entity random errors, respectively.

The next step in our empirical investigation was to analyse the response of residential rents to short-term changes in Airbnb densities. We believe that it is necessary to analyse each neighbourhood separately through the use of multiple time-series datasets, because Airbnb penetration is likely to have heterogeneous short-term impacts across different cities and neighbourhoods depending on their locational and demographic characteristics. Unit root tests were performed to check the stationarity of all variables both at the level and at the first difference. The results are reported in Table 4. Although most of the variables are not $I(0)$, all of them are $I(1)$, which means estimating first differenced models by using the OLS regression method will not lead to spurious regression problems. These first differenced models can ‘help stabilise the mean of a time series by removing changes in the level of a time series, therefore eliminating (or reducing) trend’ (Hyndman and Athanasopoulos 2018). Additionally, the first difference approach offers many other benefits. Firstly, according to Wooldridge (2018), if homoscedasticity is assumed, using a first differenced model will result in a more efficient estimate of the coefficients when compared to a fixed effects model, the most common alternative. As will be discussed in further detail, the assumption of serially uncorrelated error terms holds in this model. Additionally, the procedure can remove or reduce the presence of autocorrelation, whereby the residuals of the model are not independent from one another, often caused by a common exogenous element being present in a given time period. First differencing removes this correlation by removing the fixed effects, or time invariant portion of the error terms

$$\Delta Y_{i,t} = \alpha + \beta_1 \Delta \text{Airbnb1}_{i,t} + \sum_{j=1}^k \alpha_j \Delta x_{j,i,t} + \varepsilon_i \quad (3)$$

$$\Delta Y_{i,t} = \alpha + \beta_1 \Delta \text{Airbnb2}_{i,t} + \sum_{j=1}^k \alpha_j \Delta x_{j,i,t} + \varepsilon_i, \quad (4)$$

where $\Delta Y_{i,t}$ is the first differenced ZRI in neighbourhood i at month t ; $\Delta \text{Airbnb1}_{i,t}$, $\Delta \text{Airbnb2}_{i,t}$ and $\Delta x_{j,i,t}$ are the first difference of $\text{Airbnb1}_{i,t}$, $\text{Airbnb2}_{i,t}$, and $x_{j,i,t}$, respectively. Rather than regressing the ZRI in neighbourhood i at month t against the corresponding Airbnb density measures and time-varying characteristics, the model now regresses the change in ZRI against the change in Airbnb densities and time-varying characteristics across two consecutive time periods in neighbourhood i . In terms of interpretation, this model allowed us to quantify the effect that a month to month change in Airbnb density has on the month to month change in ZRI, as characterised by β_1 in both sets of models. We used a stepwise selection algorithm that creates models which include the relevant Airbnb density metric and only those first differenced time-varying characteristics that have a significant effect on the first difference of the ZRI. This procedure allows the first differenced models to exclude independent variables that have insignificant effects on the changes in the ZRI from month to month and, therefore, helped the paper to better isolate Airbnb’s short-term impact on rents.

Table 4. Unit Root Test Results (level and first differenced series).

City	N	ZRI	Airbnb1	Airbnb2	Number of Listings in City	Total Housing Stock	Total Vacant Housing	Unemployment Rate	Median Salary (\$)	% of Workforce with Bachelors or Higher Degrees	Poverty Level
<i>Level</i>											
Fenway, Boston	18	−1.98	−1.19	−1.49	0.41	−5.70 ***	−3.04 **	0.08	−0.22	0.0001	−7.86 ***
Logan Square, Chicago	22	−1.46	−2.02	−1.98	−1.84	−9.54 ***	−0.04	−7.99 ***	−0.22	−0.58	−6.33 ***
Venice, LA	27	−2.01	−1.38	−1.41	−0.40	−3.46 **	−4.90 ***	−0.70	0.76	0.26	−5.46 ***
Greenpoint, NYC	24	−1.12	−2.35	−2.45	−1.86	0.29	−10.3 ***	−9.56 ***	0.07	−0.06	−1.57
Rittenhousen Square, Philadelphia	19	−1.08	−0.95	−1.26	−1.44	1.77	−3.79 ***	−10.17 ***	−0.41	−1.36	−6.00 ***
Northwest, Portland	21	−0.02	−3.74 ***	−2.78 *	−3.40 **	−5.12 ***	−8.09 ***	−16.5 ***	−0.41	−0.22	−3.88 ***
La Jolla, San Diego	21	−1.57	−2.25	−2.21	−0.97	0.70	−8.11 ***	−5.57 ***	−1.53	−8.11 ***	−5.06 ***
North Beach, San Francisco	19	0.12	−4.67 ***	−2.29	−5.93 ***	2.14	2.42	−5.62 ***	1.45	1.20	1.61
Broadway, Seattle	22	0.14	−1.61	0.50	−1.23	−5.00 ***	−1.59	−5.98 ***	1.20	0.38	−6.59 ***
Georgetown, Washington DC	21	−1.63	−0.70	−0.65	−0.55	−9.69 ***	1.21	−0.13	−0.55	−1.23	1.45
<i>First Differenced</i>											
Fenway, Boston	17	−2.60 **	−2.81 **	−2.80 **	−2.56 **	−3.48 ***	−64.18 ***	−3.42 ***	−3.51 ***	−3.49 ***	−3.53 ***
Logan Square, Chicago	21	−2.87 **	−4.36 ***	−4.37 ***	−4.39 ***	−2.67 **	−3.66 ***	−2.42 **	−2.24 **	−2.24 **	−2.35 **
Venice, LA	26	−2.82 **	−7.94 ***	−8.03 ***	−7.15 ***	−3.36 ***	−2.48 **	−3.40 ***	−2.85 **	−3.32 ***	−9.37 ***
Greenpoint, NYC	23	−2.46 **	−4.29 ***	−3.64 ***	−4.44 ***	−2.29 **	−3.68 ***	−3.40 ***	−2.67 **	−2.13 **	−2.73 **
Rittenhousen Square, Philadelphia	18	−2.23 **	−5.14 ***	−5.57 ***	−4.71 ***	−2.48 **	−52.57 ***	−2.66 **	−2.47 **	−2.48 **	−2.73 **
Northwest, Portland	20	−7.02 ***	−7.37 ***	−5.90 ***	−6.62 ***	−2.52 **	−2.68 **	−13.84 ***	−2.53 **	−2.52 **	−3.26 ***
La Jolla, San Diego	20	−2.68 **	−5.07 ***	−5.20 ***	−3.51 ***	−2.72 **	−2.77 **	−4.22 ***	−2.66 **	−2.72 **	−2.77 **
North Beach, San Francisco	18	−3.16 ***	−4.37 ***	−4.30 ***	−3.06 ***	−2.92 **	−3.47 ***	−3.46 ***	−2.60 **	−3.18 ***	−2.88 **
Broadway, Seattle	21	−1.95 **	−5.33 ***	−4.37 ***	−3.74 ***	−2.24 **	−3.46 ***	−3.21 ***	−2.74 **	−2.15 **	−2.39 **
Georgetown, Washington DC	20	−2.15 **	−3.23 ***	−3.22 ***	−3.13 ***	−3.78 ***	−4.13 ***	−3.18 ***	−3.62 ***	−2.77 **	−2.76 **

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

4. Results and Discussion

The results of panel regression are given in Table 5. We found that both Airbnb densities have a significant and positive impact on the Zillow rent index. In the long run, an increase in Airbnb density causes local rents to increase too. Although the statistical significance of control variables varies between the two models, their coefficient estimates have the same sign. Specifically, employment rate and median salary have significant negative impacts on Zillow rent index in both models; the negative effect of total housing stock and the positive relationship between poverty level and residential rents are statistically significant in Model (2) only; the positive effect from number of listings in city and the percentage of workforce with higher education is significant in Model (1) only. Fisher-type panel unit root tests based on augmented Dickey-Fuller test were performed on the residuals of both models. Four methods proposed by Choi (2001) were used in the tests, all of which strongly reject the null hypothesis that all the panels contain unit roots. We concluded that higher Airbnb densities cause the neighbourhoods' rent levels to increase in the long run.

Table 5. Random Effects Panel Regression Results.

	Model (1)	Model (2)
Intercept	5051.9111 ***	6193.6094 ***
Airbnb1	6023.9382 ***	
Airbnb2		627.6814 ***
Number of listings in City	0.0130 **	0.0102
Total housing stock	−0.0579	−0.1300 **
Total vacant housing	0.0846	0.2821 ***
Unemployment rate	−7121.2346 ***	−9121.1506 ***
Median salary (\$)	−0.0211 ***	−0.0180 ***
% of workforce with bachelors or higher degrees	1861.3594 ***	1037.3335
Poverty level	1476.1232	2274.8055 **
Hausman χ^2 (p-value)	0.42 (0.9808)	1.06 (0.9003)
Panel Unit Root Test		
(Fisher-type augmented Dickey-Fuller test)		
Inverse χ^2 (p-value)	44.7605 (0.0012)	44.2980 (0.0014)
Inverse normal (p-value)	−3.2211 (0.0006)	−3.0816 (0.0010)
Inverse logit (p-value)	−3.2948 (0.0009)	3.2055 (0.0011)
Inverse χ^2 (p-value)	3.9150 (<0.0001)	3.8419 (0.0001)
N	254	254
RMSE	90.8544	91.9468
χ^2	129.1507	120.6037
p-value	<0.0001	<0.0001

Note: *** $p < 0.01$; ** $p < 0.05$.

The results from both sets of first differenced models are presented in Tables 6 and 7. The disaggregated analysis at the city level reveals some interesting patterns across the ten cities. Firstly, in line with the long-term analysis findings in Table 5, the majority of neighbourhoods exhibit a positive relationship between Airbnb density and rents, as seen from the positive coefficients associated with the density measures. That is, in most cases, a monthly increase in Airbnb density rates that resulted in an increase in the expected Zillow Rent Index in the given neighbourhood. Furthermore, when examining Airbnb penetration as a proportion of the total housing stock, three of the ten neighbourhoods—being Fenway, Logan Square, and North Beach—exhibit a relationship that is statistically significant at the 1% confidence level.

Table 6. Results using Airbnb density as a proportion of the total supply of housing.

City	Fenway, Boston	Logan Square, Chicago	Venice, LA	Greenpoint, NYC	Rittenhouse Square, Philadelphia	Northwest, Portland	La Jolla, San Diego	North Beach, San Francisco	Broadway, Seattle	Georgetown, Washington DC
Intercept	3.24	−13.05 **	40.72 *	−1.74	8.04	−45,871.96 *	142.22 ***	−1707.19 ***	3.74	9.35
Airbnb1	4460.19 **	31,299.19 ***	7.71	−719.5	−1419.54	3160.86	3005.62	58,812.12 ***	4899.93	−6743.13
Number of listings in City		−0.05 ***						−0.13 **		
Total housing stock						1492.42 *		20.00 **		
Total vacant housing				−0.45 *		−84.02 ***	13.7 ***			
Unemployment rate	3277.58	−12,370.93 ***				−8,426,990.24 *	141,876.29 ***	−1,253,372.6 ***		
Median salary			−0.04 **							
% of workforce with bachelor's or higher						8,009,357.74 *		628,373.09 ***		
Poverty level					2967.97 **	9172.82 ***	−385,971.61 ***			
R ²	0.35	0.66	0.16	0.14	0.32	0.82	0.90	0.75	0.08	0.02
Adjusted R ²	0.28	0.61	0.09	0.08	0.24	0.76	0.88	0.69	0.03	−0.03

Note: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.**Table 7.** Results using Airbnb density as a proportion of the vacant supply of housing.

City	Fenway, Boston	Logan Square, Chicago	Venice, LA	Greenpoint, NYC	Rittenhouse Square, Philadelphia	Northwest, Portland	La Jolla, San Diego	North Beach, San Francisco	Broadway, Seattle	Georgetown, Washington DC
Intercept	3.5	−14.3 **	40.64 *	−1.31	8.00	−45,485.37 *	142.67 ***	−1602.4 ***	2.43	9.45
Airbnb2	590.42 **	3407.88 ***	6.2	−61.39	−189.13	263.89	425.98	7601.54 ***	296.07 *	−702.68
Number of listings in City		−0.05 ***						−0.15 ***		
Total housing stock						1479.37 *		18.53 **		
Total vacant housing				−0.46 *		−84.15 ***	13.76 ***			
Unemployment rate		−12,675.23 ***				−8,348,757.25 *	142,468.8 ***	−1,183,308.56 ***		
Median salary			−0.04 **							
% of workforce with bachelor's or higher						7,945,874.66 *		593,580.91 ***		
Poverty level					3116.31 **	9267.79 ***	−387,672.23 ***			
R ²	0.27	0.66	0.16	0.14	0.32	0.82	0.90	0.77	0.17	0.02
Adjusted R ²	0.24	0.61	0.09	0.08	0.25	0.76	0.88	0.71	0.12	−0.03

Note: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Additionally, when examining Airbnb density as a proportion of a neighbourhood's vacant supply of housing, four of the ten neighbourhoods show a significant positive relationship between Airbnb usage and rents. These results are consistent with both the supply side theory mentioned previously and Airbnb's hypothesised stock reallocation effects. More specifically, the home-sharing premium results in an increased number of Airbnb units available relative to the number of vacant dwellings, which puts upward pressure on rents due to the fact that some of the supply of long-term accommodation has been reallocated to the short-term market.

This being said, however, the relationship is far from unanimous. Consistent with the findings of [Garcia-López et al. \(2019\)](#), the large variance in values of Airbnb density coefficients indicates that home-sharing has had heterogeneous effects on neighbourhoods' rental markets. Using the first density metric, the models indicate that a one-unit monthly increase in Airbnb density rates can increase the ZRI by anywhere between 7.71 dollars, in the case of Venice, and 58,812 dollars, in the case of North Beach. The variance is similar when using the density measure as a proportion of vacant stock, as coefficients range from 6.2 dollars in Venice to 7601 dollars in North Beach. Whilst the upper end of this spectrum is suspiciously high, it is important to note that at the end of the research period, North Beach had a density measure of just 0.94%. Therefore, whilst an increase of \$7601 is high, a one percentage point increase in Airbnb density could indeed have a large effect on the rental index in the neighbourhood.

Additionally, when examining the maturity of the Airbnb markets in these neighbourhoods, an obvious pattern emerges. As expected, the neighbourhoods with the highest Airbnb density rates at the end of the research period are also those where β_1 is the lowest, in absolute terms. That is, when Airbnb units already account for a large proportion of the total and vacant stock of housing, a one-unit monthly increase in the Airbnb density measures will change the ZRI the least, both positively and negatively.

Interestingly, the neighbourhoods that exhibit a significant positive relationship between Airbnb density rates and rents are also those with some of the highest population densities; this being Fenway, Logan Square, and North Beach. This relationship may be due to the fact that the housing markets in these neighbourhoods are already saturated and under strain. However, due to the small sample size of neighbourhoods analysed, it is difficult to comment on the broader relationship between population densities and the impact that Airbnb has on rental markets.

In terms of the time-varying characteristics included in our models, it becomes apparent that few affect the level of rents in a consistent manner. As can be seen from both tables, the use of the stepwise selection procedure has meant that some neighbourhoods' models include many more time-varying characteristics than others. Additionally, many of the variables that were included have inconsistent signs, contradicting previous research and perhaps underlining one limitation of the first differenced models. Furthermore, the models' ability to explain the variation in monthly changes in the ZRI differ dramatically: in some neighbourhoods, the first differenced model explains 90% of the variation in ZRI values, as can be seen from La Jolla, whilst in others, such as Broadway, it explains just 8%. Thus, whilst in some neighbourhoods these first differenced models are relatively successful in estimating ZRI levels, they are far from being a perfect predictor.

5. Policy Implications

Despite the recent scholarly investigations into Airbnb's effects on rental markets, policy makers tasked with regulating the unprecedented growth of home-sharing platforms have had inadequate information with which to make effective 'informed' policy decisions ([Horn and Merante 2017](#)). Rather than using evidence-backed approaches, they have often relied on the recommendations of academics in order to 'curb Airbnb's impacts on a neighbourhood's character and housing while harnessing the economic activity it brings' ([Lee 2016](#), p. 229). This has led to attempts at regulation across cities differing in both approaches and aims. On one end of the spectrum, policymakers have looked to engage in the free market 'laissez-faire' approach whereby they have not engaged in regulation or

have done so in collaboration with these home-sharing platforms. On the other end are policies that have used existing planning regulations in order to restrict growth or entirely curb the operation of the platforms (Ferreri and Sanyal 2018). Examples of attempts at regulation in cities across the world include: a requirement to have a specific permit (Barcelona, Berlin, Paris, and San Francisco), paying an increased rental tax (Amsterdam and San Francisco), and outlawing STRs or restricting the number of days that they can be in operation (Berlin, New York, and Amsterdam) (Garcia-López et al. 2019). It is also important to note that the vast majority of policies implemented by governments in the past have been backwards looking; that is, they have looked to mend the negative effects that Airbnb has had on their rental markets rather than curb its future impact.

In order to lessen the negative impact Airbnb has on housing whilst still harnessing its economic potential, a policy recommendation must take into account several factors. Firstly, as examined earlier, Airbnb's heterogeneous effect at the neighbourhood level means that no single policy measure can be implemented to address the effects associated with the home-sharing platform. Rather, each policy recommendation must be tailored specifically to a district or neighbourhood. Secondly, whilst it is tempting for governments to create policy measures that look to treat Airbnb's past impacts, it is likely that these effects will change as the platform matures and therefore makes it important to forecast future impacts. Finally, whilst home-sharing platforms often exacerbate the affordability issues present in many neighbourhoods, it is important that governments look to solve the root cause of this problem if they want to help their local residents by facilitating the creation of a more equitable housing market in the future.

In response to the positive correlation between Airbnb penetration and rents, policy makers and academics have often suggested a blanket ban on home-sharing platforms and STRs. With this in mind, Koster et al. (2018) attempted to assess the effectiveness of Home Sharing Ordinances (HSOs), a type of ban, in Los Angeles' housing market. More specifically, the researchers analysed the change in Airbnb penetration as well as rental rates in areas close to the borders of cities that had implemented the HSOs. In effect, they replicated a controlled experiment in order to quantify the policy's effects. They found that HSOs were indeed effective at reducing the number of Airbnb listings, with the policy lowering the number of 'entire flat' listings by almost 50% in the long run. Additionally, in using a differences-in-differences estimation, they were able to show that, on average, the HSOs were able to reduce rents in the cities by 2%. This being said, however, this type of policy has little impact on the larger issue. This is evidenced by Lee (2016), who used qualitative interviews as well as economic theory to argue that, whilst a blanket ban on STRs would remove Airbnb's role in Los Angeles' affordability crisis, it would also deprive the city of the economic benefits associated with STRs and would not help increase the stock of affordable housing.

Instead of an outright ban, a more appropriate measure could be a system of taxation that solely targets commercial operators. This would enable local governments to generate revenues, in the form of occupancy tax, from the incomes earned by commercial operators, who are often accused of knowingly evading taxes through the use of these home-sharing platforms. Not only would the policy deter the commercial use of Airbnb whilst still allowing local landlords to rent out their excess space, but the tax revenue generated could help fund the development of additional affordable housing units and target the larger problem at hand.

Furthermore, policy makers should consider using geographically targeted restrictions which would only allow Airbnb STRs in buildings that meet a target affordability threshold, as proposed by Lee (2016). Theoretically, this policy should incentivise large commercial operators to subsidise rents in some of their units so that they are able to rent out others in the short-term market and tap into the home-sharing premium. Additionally, Lee (2016) also argues for the use of Community Benefit Agreements (CBAs), which are contracts that allow for the use of Airbnb if certain conditions are met, usually to do with the creation, or the setting aside, of affordable housing units. He argues that this would remove pressure on rents due to Airbnb, allow cities to benefit from the economic efficiencies of short-term renting, and simultaneously increase the stock of affordable housing (Lee 2016).

Finally, it is important to note that some neighbourhoods may actually benefit from the operation of Airbnb, if regulated in a responsible manner. Policies should be designed to incentivise the listing of ‘shared room’ or ‘whole room’ listings rather than ‘entire unit’ ones as these STRs can help local residents earn additional income from renting out their excess capacity. Such a policy would be in line with Airbnb’s original purpose and would help protect the local rental market from commercial operators. None the less, there are still ways commercial operators can manipulate this system in order to benefit at the expense of local landlords. It is therefore important that strict monitoring systems, similar to the ones used in the hotel industry, are implemented in the home-sharing economy.

6. Conclusions

The rapid growth in home-sharing platforms has recently gathered interest from both academics and policy makers, leading to a heated debate on the platforms’ effects on the cities in which it operates. In response to this debate, this paper has looked to examine the long-term relationship and short-term dynamics between Airbnb densities and rents in ten neighbourhoods in the U.S. We collected monthly time series data from ten large American cities between 2013 and 2017 to form a panel dataset. Our random effect panel regression model analysis suggests that there exists a long-run positive relationship between Airbnb densities and the Zillow rent index. To investigate the short-term dynamics between Airbnb densities and rents, we estimated first differenced models for the ten cities separately. Although the findings are largely consistent with the long-term analysis results, there are considerable variations in the magnitude of the impacts from Airbnb density monthly changes on Zillow rent index monthly changes. The short-term analysis highlights the importance of using disaggregated data because Airbnb penetration is likely to have heterogenous short-term impacts across different cities and neighbourhoods depending on their locational and demographic characteristics.

Our study has added to the limited existing literature in numerous ways. Firstly, by examining the relationship between home-sharing and rental rates at a zip code level, this paper has been able to uncover invaluable insights that otherwise go missed. That is, the use of several time-series datasets has shown that the unanimous positive relationship between Airbnb penetration and rents found in the majority of past papers is misleading. Rather, the results of this paper suggest that the relationships differ across neighbourhoods depending on their numerous individual characteristics. Secondly, the use of first differencing has allowed for a new interpretation of results. This paper has used a one-month time-lag to examine how a change in Airbnb density rates from month to month changes the corresponding neighbourhood’s immediate level of rental rates. Furthermore, the use of first differenced time-varying characteristics has allowed for a more accurate estimation of Airbnb’s impact on real estate markets. Finally, this paper has set out advice to policy makers tasked with checking Airbnb’s future growth. The heterogenous impact of Airbnb means that policies need to be adapted to the specifics of a neighbourhood. Additionally, whilst many policy makers have championed the use of an outright ban, this does little to target the larger issue. Instead, law makers should look at geographically targeted policies that make use of Airbnb’s economic efficiencies whilst increasing the overall stock of affordable housing available to local residents.

However, this paper does not come without limitations. More specifically, whilst the paper tries to account for time-varying characteristics that may influence the ZRI of a neighbourhood without affecting the Airbnb density measures used, there will of course be sources of bias that have not been accounted for. Additionally, the hand selection of the ten neighbourhoods analysed may result in an unfair view of Airbnb’s effect on rental markets. Therefore, this paper emphasises that the results found using these models should not be extrapolated to other neighbourhoods or metropolitan areas due to Airbnb’s unique effects. Finally, the fact that many of the first differenced models employed here are only able to explain a portion of the variation in ZRI suggests that perhaps the models may suffer from omitted variable biases. This is one of the most challenging aspects of our study, and studies on home sharing in general. As home sharing is a relatively new phenomena, the quantity and quality of data available for scientific research leave much to be desired. This will change as the sector grows.

Further research should look into more available data sources that can support the use of advanced statistical methods.

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