Do Airbnb properties affect house prices?

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Abstract

The growth of peer-to-peer markets has provided a mechanism through which private individuals can enter a market as small scale, often temporary, suppliers of a good or service. Companies that facilitate this type of supply have attracted controversy in cities around the world, with concerns regarding Uber and Airbnb in particular. Airbnb has been criticized for failing to pay taxes to local authorities, for avoiding regulatory oversight that constrains more traditional suppliers of short-term accommodation, and for the impact of short-term rental properties on the value of residential property. A report prepared by the Office of the Attorney General of the State of New York lists these impacts among a number of concerns: do Airbnb rentals provide a black market in unsafe hotels? Do short-term rentals make New York City less affordable? Is the influx of out-of-town visitors upsetting the quiet of longstanding residential neighborhoods?

These concerns pose difficulties because they imply different impacts on the values of residential properties. If short-term rentals provided via Airbnb create a concentration of what are effectively unsafe hotels or upsetting quiet residential neighborhoods, they would generate a local concentration of externalities that might be expected to depress property values rather than make housing less affordable. Alternatively, if negative externalities are modest relative to the impacts of space diverted from providing housing for residents to providing short-term accommodation for visitors, then local concentration of Airbnb properties may increase house prices. In this paper we present an evaluation of the impacts of Airbnb on residential property values in New York City.

1 Introduction

Since its founding in 2008, Airbnb's rapid growth has prompted the expression of concerns about its impact on cities and urban housing markets. These concerns have focused on a variety of issues, ranging from whether Airbnb clients are paying appropriate fees and taxes to the appropriateness of listing residential properties in the occupied territories of Israel. Perhaps no concern has been more vehemently expressed than the impact of Airbnb listings on housing affordability. This issue led to ballot initiative Proposition F in 2015 in San Francisco, with a group of protesters occupying Airbnb headquarters in San Francisco in advance of the vote. It has also led to bans or partial bans on advertising of short-term private rentals in Barcelona, Berlin and other cities around the world.

Airbnb is an internet-based peer-to-peer marketplace that allows individuals to "list, discover, and book" over 3,000,000 accommodations in over 65,000 cities across the world (Airbnb 2017). Airbnb acts as an intermediary between consumers and producers to reduce the risk and cost of offering a home as a short-term rental, which enables suppliers (homeowners) to flexibly participate in the commercial market for short-term residential housing. While Airbnb was not the first service to act as an intermediary in this way, and even today has competition in provision of these services, its success and rapid growth have made it the focus of concern for policy makers.

Airbnb is part of what has come to be known as the "Sharing Economy," a term that refers to peer-to-peer products, services, and companies. A large part of the motivation behind the Sharing Economy, according to the companies that self-define as part of the sector, is to make use of otherwise under-utilized goods.[1] In the case of housing, homes might not be utilized to their full extent (for example, during vacations or due to an unused bedroom). This allows homeowners to "share" (e.g., rent) parts or the entirety of their homes during these times and earn revenue. The potential for and ease of these types of transactions is greatly increased by better matching technologies, a trend which has been driven by the Internet (Horton & Zeckhauser 2016). Airbnb further reduces transaction costs for both consumers and producers by providing a feedback and reputation mechanism, allowing for a safer and more streamlined transaction.

Despite Airbnb's efficiency improvements and the ability it gives homeowners to generate revenue, there

[1] See "The Sharing Economy: Friend or Foe?" (Avital, Carroll, Hjalmarsson, Levina, Malhotra & Sundararajan 2015) for a concise summary of the different viewpoints surrounding the future of the Sharing Economy.

are concerns about the economic and welfare effects of Airbnb's presence on the residential housing market.[2] The analysis belows presents an examination of some of those economic effects. The study is motivated by the following question: in a highly constrained and regulated housing market, where residential homes are both in high demand and located in dense neighborhoods, what is the impact of being able to transform residential properties into revenue streams and partly commercial residences?

In New York City, the question of impact on housing affordability has been raised explicitly, and the role of Airbnb has been at the center of a number of policy discussions at the municipal level. In 2014, the Attorney General of New York State, Eric Schneiderman, investigated Airbnb's presence in New York City (Schneiderman 2014). The subsequent report indicated that 72% of Airbnb listings in New York City violated property use and safety laws and were therefore illegal.[3] The Attorney General's Office also found that over 4,600 units in New York City were booked for more than three months of the year, leading the Attorney General's Office to question the impact that Airbnb has on the supply of housing stock and the affordability of housing in New York City.

The prospect that Airbnb encourages violation of health and safety laws as well as reduces housing supply raises a puzzle regarding the likely effects on house prices. If short-term rentals provided via Airbnb create a concentration of what are effectively unsafe hotels, upsetting quiet residential neighborhoods with more traffic and persons who don't care about the neighborhood, they may generate a local concentration of externalities that might be expected to depress property values. Alternatively, if these externality effects are not present or are modest relative to the impacts of space diverted from providing housing for residents to providing short-term accommodation for visitors, then local concentration of Airbnb properties may increase house prices.

Perhaps because of this confusion, it is possible to find divergent viewpoints expressed about the impacts of Airbnb in the popular press and in consultant reports. Most policy makers appear to believe that Airbnb causes housing prices to increase. In October of 2016, New York Governor Andrew Cuomo signed into law a bill providing for a range of fines to be imposed on those who advertise entire apartments or dwellings

[2] There are several firms similar to Airbnb. As these types of companies become more prevalent and continue to expand, this area of research becomes increasingly important, as such firms mostly enter highly constrained and regulated markets, the dynamics of which often have welfare consequences. The analysis here is not directly applicable to, for example, understanding the economic impact of Uber on a city, a ride-sharing service. However, the research presented in this paper suggests that these companies can have a significant impact, one worthy of study.

[3] This is largely due to New York State's Multiple Dwelling Law, which imposes strict regulations on safety and health conditions that must be met as well as limits on business uses of homes.

for time periods of less than 30 days. The issue of the impact on house prices was presented as a central argument for passage of the law, as noted in Brustein & Berthelsen (2016):

> Liz Krueger, the state senator who sponsored the bill, said in a statement that the passage was a "huge victory for regular New Yorkers over the interests of a $30 billion corporation." She has argued that Airbnb has actively encouraged illegal activity, taking apartments off the rental market and **aggravating the city's affordable housing crisis**.

The response of Airbnb was to characterize the law as a policy designed to protect the hotel industry rather than concern over housing affordability. Brustein & Berthelsen (2016) go on to report that:

> Airbnb says New York lawmakers had ignored the wishes of their constituents. "Albany backroom dealing rewarded a special interest – the price-gouging hotel industry – and ignored the voices of tens of thousands of New Yorkers," Peter Schottenfels, a spokesman for the company, said in a statement.

At the time of the Attorney General's investigation in 2014, Airbnb had experienced an increase of over 1000% in both listings and bookings from 2010 to 2014. To understand Airbnb's scale of growth, or at least the way their investors value its business, an oft cited statistic is that in its most recent funding round, Airbnb was valued at approximately $31B. This suggests it is more valuable than Marriott International Inc., which has a market capitalization of $17.9B and which owns over 4,000 hotels. In 2014, Marriott International Inc. had $13.8B in revenue, over ten times Airbnb's *projected* revenue in 2015 (Kokalitcheva 2015) [4]. That investors are still willing to purchase an equity stake in Airbnb at its current valuation suggests an expectation of continued, extraordinary growth. Their expected revenue for 2020 is $10B, implying an annual growth rate of approximately +75% (Kokalitcheva 2015).

Confronted by such rapid growth, the New York Attorney General's investigation is typical of concerns about the presence of Airbnb in cities across the world. Central to this consideration, according to author Doug Henwood, is the potential of Airbnb's, "real, if hard-to-measure, impact on housing availability and affordability in desirable cities," (Henwood 2015). We will argue below that almost all of the welfare consequences (both positive and negative) of Airbnb circle around the question of its impact on housing

[4] Although Airbnb's total revenue for the third quarter of 2017 was estimated at more than $1 billion, so its continued growth is making it a serious rival to major hospitality firms.

prices. Our analysis examines the question of Airbnb's impact in the context of New York City by presenting both empirical evidence and theoretical arguments that help us to understand Airbnb's impact on residential housing prices – an issue that has been raised frequently but rarely studied carefully. This paper seeks not to make a judgment on whether or not Airbnb is *good* or *bad* for cities (which in any event would depend critically on which population was being considered), but rather to provide the first quasi-experimental estimates of Airbnb's impact on neighborhood residential housing prices by focusing on the case of New York City.

In New York City, Airbnb activity tends to be heavily concentrated in the boroughs of Manhattan and Brooklyn, with some concentration in portions of Queens that are close to La Guardia airport or have good access to Manhattan. As of November 17th, 2015, there were a total of 35,743 active listings in New York City. These listings constitute a sizable portion of the accommodations industry in New York City, as there is a total of approximately 102,000 hotel rooms in the entire city (Cuozzo 2015).[5] Airbnb has an apparently significant presence in New York City and many other cities across the world. The question is whether making these properties available to a population not normally resident in the city has an impact on prices and, if so, whether the effect is to increase or decrease prices.

2 Contemporary Policy Debates and Literature

Residents of cities and local governments across the world, both in favor and against Airbnb's presence, are growing increasingly vocal. The arguments against Airbnb focus primarily on three areas:[6] 1) Airbnb's impact on decreasing affordability, 2) the negative externalities caused by Airbnb guests,[7] and 3) the shadow

[5]There are 3,394,486 housing units in New York City measured in 2013 (Been, Capperis, Roca, Ellen, Gross, Koepnick & Yager 2015), meaning that over 1% of housing units were being actively listed on Airbnb on November 17th, 2015. Given that the distribution of Airbnb is not normally distributed throughout the city, we should expect that in some areas, the ratio of Airbnb listings to total units is significantly higher.

[6]An article on the impact of Airbnb in Los Angeles articulates these concerns clearly: "Airbnb forces neighborhoods and cities to bear the costs of its business model. Residents must adapt to a tighter housing market. Increased tourist traffic alters neighborhood character while introducing new safety risks. Cities lose out on revenue that could have been invested in improving the basic quality of life for its residents. Jobs are lost and wages are lowered in the hospitality industry" (Samaan 2015, p. 2).

[7]Horton describes this phenomenon well: "If Airbnb hosts bringing in loud or disreputable guests but, critically, still collect payment, then it would seem to create a classic case of un-internalized externalities: the host gets the money and her neighbors get the noise" (Horton 2014, p. 1). Recently Airbnb has even been criticized in Whyte (2017) for the problem of "overtourism" which we are assured is a "very real" problem, despite its similarity to the complaint that one's favorite restaurant now requires reservations. We can understand this as a problem in the sense that increasing tourists is effectively increasing urban population, which in a *closed-city* model reduces equilibrium utility levels.

hotel industry that allows commercial operators to use Airbnb in order to evade important safety regulations and taxes.[8] On the other side, those who argue in favor of Airbnb's presence tend to focus on its positive economic impact on the city, including creating new income streams for residents as well as encouraging tourism and its associated economic benefits for a city (Kaplan & Nadler 2015).

The contemporary policy debates surrounding Airbnb can be summarized by the following question: should Airbnb be regulated and, if so, what is the appropriate type and level of regulation? This has been debated in New York City Council Hearings, protests have formed in support of and against Airbnb, and this past November (2015), Airbnb even made it onto the ballot in San Francisco through *Proposition F*.[9] There is strong language on both sides; some are scared of Airbnb's impact on the affordability of neighborhoods and others suggest that its net welfare effects are positive. Additionally, the policy debates surrounding Airbnb and other sharing economy companies are concerned that these companies degrade important regulations. Arun Sundararajan argues that new regulations need to be developed to protect individuals, both consumers and workers, as a result of these companies: "As the scale of peer-to-peer expands, however, society needs new ways of keeping consumers safe and of protecting workers as it prepares for an era of population-scale peer-to-peer exchange" (Sundararajan 2014).

In the New York City Council hearings, as well as in protests and debates in the public sphere, there is a lack of data and analysis upon which people can rely. Because of this void, arguments are, to put it bluntly, mostly rhetorical and ideological rather than empirical. Thus, in addition to pursuing the analysis of Airbnb's impact on housing prices in New York City, the data collection work included in this paper will also hopefully begin to fill that void so that individuals can better understand Airbnb's impact in a way that is mathematically rigorous and econometrically robust.

To our knowledge there is only one other careful scientific study that estimates the direct impact of Airbnb rental availability on house prices. Barron, Kung & Proserpio (2017) examine the impacts of Airbnb listings on the value of house price and rent indices in US cities. Their analysis, working as it does with aggregate (zip-code level) price trends, must deal with the potential endogeneity of the number of Airbnb listings. They deal with this by constructing an instrument based on Google Trends searches for Airbnb.

[8]Much of the uproar in New York City concerns non-uniform taxation and regulation; hotels and motels face taxes which Airbnb is not currently subject to. In New York City, it is up to hosts to pay taxes on the revenue they generate from Airbnb. In some other cities, Airbnb has a "collect and remit" feature to collect taxes.

[9]*Proposition F* was ultimately rejected but would have limited the number of nights an Airbnb could be available each year.

Unfortunately, these are not accurately available at the zip code level, so to obtain an instrument that varies at the zip code level they interact these searches with a measure based on the number of food service and lodging establishments in the zip code area. Whatever objections might be raised concerning the instruments, they do find that an increase in Airbnb listings is associated with an increase in house prices and rents.

2.1 Research on Peer-to-Peer Platforms

Compared with research on housing markets and how their organization affects price outcomes, there is even less literature on the economics and impacts of peer-to-peer Internet markets. The existing literature provides a basis for addressing two main questions: 1) In what ways do peer-to-peer markets create economic efficiencies? 2) How do peer-to-peer platforms impact markets in auxiliary ways (e.g. over and above "normal" ways of doing business)? The remainder of the literature review will be devoted to understanding some of the most important contributions in this area and its application to this paper.

Einav, Farronato & Levin (2015) review some important considerations that allow these types of markets to exist. Among other things, they highlight the difficulties associated with designing these markets, such as search, trust and reputation, and pricing mechanisms. We will review a few of the important findings in the way they relate to Airbnb.

Einav et al. (2015) review some of the policy and regulatory issues that arise in the context of peer-to-peer markets, such as the dichotomy that local businesses are often subject to certain entry and licensing standards (such as limits on residential short-term rentals), while companies like Airbnb are often able to evade these regulations. There is not a clear solution to these issues. On the one hand, one might argue that these regulations are an important response to market failures (Einav et al. 2015, p. 19), while others might argue these regulations reduce competition by favoring incumbents. As has been expressed, an important motivation of this paper is filling the void in quantifying the impact of one peer-to-peer market. Einav et al. (2015) makes clear that grappling with these regulatory quandaries requires empirical work: "the effect of new platforms for ride-sharing, short-term accommodation or other services on prices and quality, and their consequences for incumbent businesses, are really empirical questions" (Einav et al. 2015, p. 19).

Peer-to-peer markets, like Airbnb, face tremendous obstacles in having to match buyers and sellers. One of the difficulties is balancing a breadth of choice with low search and transaction costs. As such, Airbnb provides users (those looking for lodging) with a simple search mechanism with quick results, allowing these users to *then* filter more selectively based on desired criteria, like exact neighborhood, number of rooms, or price. In terms of pricing mechanisms, Airbnb allows its hosts to adjust their own prices, rather than set prices based on market conditions as is done for companies like Uber and Lyft.

An important question that Airbnb must grapple with is how to facilitate trust between users and hosts on the platform. The way Airbnb deals with this is through their reputation mechanism, which allows both hosts and guests to review each other. Trust in the platform depends on the success of the reputation mechanism.[10]

Levin (2011) highlights a few of the most distinctive characteristics of peer-to-peer markets and then delves into some of the economic theory applied to these types of markets . One particularly relevant feature that he highlights is the ability for these types of markets to facilitate customization, which has the potential to lead to a superior matching process between buyers and sellers. The paper reviews a wide body literature on different elements of internet markets. Varian (2010) also reviews the existing literature in this field and discusses the implications of markets moving online such as the ease of scalability, the unprecedented amount of data, and the ability for firms to experiment at significantly lower costs. Horton & Zeckhauser (2016) models a two-sided peer-to-peer market by examining the decision to own and/or rent as both short-run and long-run consumption decisions. In addition, they also conduct a survey to empirically evaluate consumers' decisions to own and rent different goods. Yet while each of these papers both review existing knowledge and provide theoretical frameworks (mostly around transaction costs), none ask the questions regarding the empirical impacts of such platforms on market values of underlying assets being used or traded in these markets.

The most relevant research to this paper is Zervas, Proserpio & Byers (2016). It is the only paper of which we are aware that attempts to quantify Airbnb's impact on local neighborhoods. Focusing on Airbnb usage in Texas, the main findings are that a 10% increase in the number of listings available on Airbnb is associated with a 0.34% decrease in monthly hotel revenues using, in their main model, a difference-in-differences design with fixed effects.[11] Their difference-in-differences design examines the difference in

[10] There exists literature on Airbnb's reputation mechanism, namely Andrey Fradkin's research, "Bias and Reciprocity in Online Reviews: Evidence From Field Experiments on Airbnb" (Fradkin, Grewal, Holtz & Pearson 2015).

[11] In cities where there is higher Airbnb penetration, they find a significantly more pronounced effect. In Austin, they find

revenues "before and after Airbnb enters a specific city, against a baseline of changes in hotel room revenue in cities with no Airbnb presence over the same period time" (Zervas et al. 2016, p. 11). In order to make a causal claim based on their estimates, they test for and assume that there is no endogeneity that drives both Airbnb activity/entry as well as hotel revenues.[12] This paper has served as a helpful resource for how to estimate the impact of Airbnb activity on the housing market, though there are of course significant and notable difference in our analysis and that of Zervas et al. (2016), the biggest of which being that we are estimating the impact on residential housing prices (in New York City) rather than hotel revenue and that we consider both a hedonic model with fixed effects as well as a difference-in-differences strategy.[13]

3 Theoretical Perspectives

In this section we present an overview of theoretical arguments that could justify an *a priori* view that Airbnb listings might have an impact on residential property values. Where possible, we identify the direction of such impacts.

3.1 Overview

The intuition for expecting Airbnb to have an impact on residential property values is relatively straightforward. First, under many circumstances residences can be held as an asset and rented via Airbnb to produce an income stream. This can permit speculating for potential capital appreciation as well as generating rental income during the period of ownership. This potential income and capital gain might both draw investors to purchase residential property not for their own use and to hold onto properties for longer because rental income obtained via Airbnb reduces the cost of ownership. Either of these mechanisms would increase effective demand for housing and drive up the price of sales and rentals on these units. This would potentially affect both freehold sales price and rental price because the willingness-to-pay of both buyers and renters would be increased due to this potential increase in income.

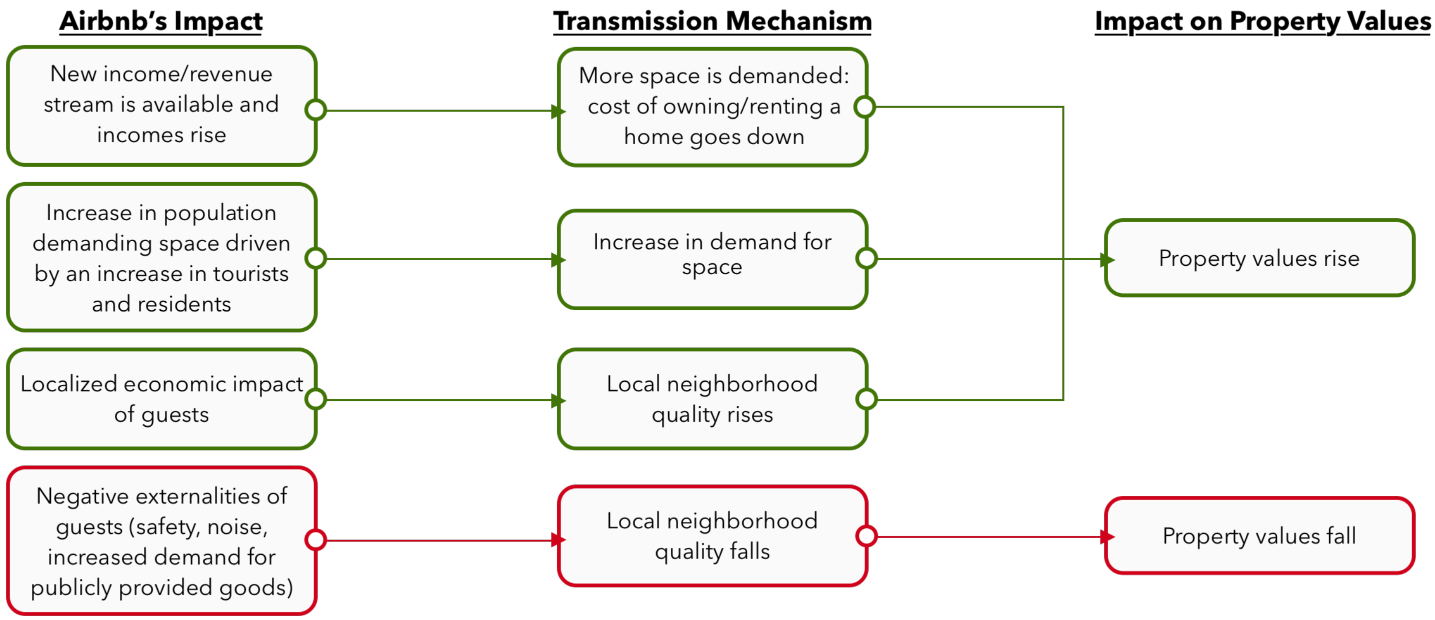
that Airbnb activity has decreased hotel revenues by 10%

[12] One thing to note about their difference-in-differences strategy is that their treatment group is defined after the first Airbnb listing enters that market. For a robustness check, they also change this treatment to be after ten and fifty Airbnb listings are available in a given location. To further test the robustness of their main specification, they also include different measures of Airbnb penetration, such as limiting their analysis to only include listings which have received at least one review.

[13] There is also ongoing research by Chiara Farronato and Andrey Fradkin, which seeks identify the impact of Airbnb activity on hotel revenues across many cities in the United States.

In terms of contemporary policy debate, this relates to the criticism that Airbnb allowed "commercial operators" on their service, a part of the findings of the New York State Attorney General's investigation,[14] which might very well impact the supply of available housing.

Figure 1: Transmission Mechanisms for the Impact of Airbnb Activity on Housing Prices



There are additional potential transmission mechanisms. For example, Airbnb units could increase local population, especially local tourist population, and generate local economic impact on businesses by increasing the demand for local goods and services. This may cause incomes to rise as well increase localized provision of amenities that provide attractive goods and services to visitors. Property values may increase both becuase of increased demand for commercial (non-residential) space, as well as localized provision of amenities for visitors. Finally, it should be noted that there are mechanisms that may cause property values to decrease. The increase in densities that come from accommodating more people, or the negative externalities (such as noise, traffic and safety concerns) caused by Airbnb guests might make living near concentrations of Airbnb units unpleasant. Finally, a difficult-to-quantify but potentially behaviorally significant factor would be the signal that creasing Airbnb availability might provide for neighborhood quality and subsequent gentrification. The emergence of concentrated provision of Airbnb units could itself induce speculative purchase of residential property in anticipation of subsequent capital gains.

[14]In the investigation, they found that 6% of short-term rentals were run by commercial operators, as defined by having more than two units on the platform, accounting for approximately 37% of revenue from New York City Airbnb listings.

In Figure 1, we outline some of these potential transmission mechanisms for how Airbnb might impact housing prices. As noted in the figure and mentioned above, there is the potential for the impacts to both increase and decrease house prices. While some of the arguments advanced in policy discussions seem to raise the possibility of impacts in both directions, impacts that increase property values and make housing less affordable are the primary focus of most discussion. In the subsections below we consider in greater detail two approaches that suggest the likelihood of this outcome.

3.2 Capitalization

Consider a city in equilibrium, with equilibrium welfare of residents is given by v. For a house located at distance x the annual rent that will be paid by a resident is then given by $R(v, x)$. Here we suppress other parameters such as transport costs t and parameters of the utility function that will obviously affect the equilibrium rent function at each location and for any given level of welfare.

There is a relationship between this annual rent at x and the structure price P which is given by:

$$P = \frac{R(v, x)}{u} \tag{1}$$

where u is the *user cost of housing*:

$$u = r_{\mathsf{rf}} + \omega - \tau \cdot (r_m + \omega) + \delta - g + \gamma \tag{2}$$

This model has been applied and discussed by Sinai & Souleles (2005) and Kuttner & Shim (2012). In the present context, we need to account for the fact that the Airbnb income is taxable income. If $\alpha > 0$ is the expected annual Airbnb rental as a percentage of house value, then we augment the expression for user cost of housing to:

$$u = r_{\mathsf{rf}} + \omega - \tau \cdot (r_{\mathsf{m}} + \omega) + \delta - g + \gamma - (1 - \tau) \cdot \alpha \tag{3}$$

with:

Variable	Interpretation
r_{rf}	Risk free annual interest rate
ω	Property tax rate as a percent of market price
τ	Effective tax rate on personal income
r_{m}	Annual mortgage interest rate
δ	Maintenance costs as a percent of market price
g	Expected percent capital gain or loss
γ	Ownership risk premium
α	Airbnb rental as a percent of market price

Essentially, this defines (or is implied by) the process of capitalization, relating the rent, property tax, mortgage and risk-free interest rates, maintenance costs, expected capital gains and ownership risk premium to the price of the structure. We need to add to this an expression that allows for the use of Airbnb as a mechanism for earning revenue from the asset.

Assuming that at least partial capitalization takes place, and that $R(\cdot) > 0$ and $\tau < 1$ we will have $\frac{\partial P}{\partial \alpha} > 0$. Assuming that owners are forward-looking, face finite interest rates, and purchase properties in competitive markets we would expect at least partial capitalization so that property values would rise.

This is perhaps the simplest theoretical perspective that implies a positive relationship between the presence of Airbnb as a service that available to property owners and the freehold price of residential property. The Airbnb service provides the opportunity to earn additional income by virtue of ownership of a residence. The present value of this income stream, available contingent on ownership, would increase the market price of properties as long as capitalization takes place.

3.3 Simple monocentric model

What are the mechanisms through which Airbnb activity might impact housing prices? This section will explore this question using an extremely simple monocentric urban model, with residential space and consumption of other goods being perfect complements. Despite its simplicity, many of the essential comparative static impacts of increased Airbnb activity can be clearly demonstrated.[15]

[15]These types of models are based on the original Ricardian Theory of Rent (1817) (DiPasquale & Wheaton 1996).

As outlined in Figure 1, there are several ways in which Airbnb activity might impact housing prices. On the demand side, we might reasonably expect that the Airbnb service provides homeowners with an increase in income and as a result, more space would be demanded. Furthermore, as a result of Airbnb, there is an increase in the population of the city demanding space or equivalently an increase in the space demanded by each household.[16] Local incomes and population may also increase if there is a localized economic impact caused by guests spending money in areas near their Airbnb listings. Finally, there might be a negative externality of guests, such as noise, decreased security, or simply additional demand for publicly provided goods (such as transportation).

These comparative-static results are formally derived and well-summarized in Brueckner (1987*a*). Within the context of a simple open-city model with all agents sharing a common utility function, he shows that an increase in population is associated with an increase in rents at all locations, and an increase in income is associated with a decline in rents for locations closer to the CBD and an increase in rents for locations further away. Because the analysis uses an arbitrary utility function, there is no single parameter that can represent an increase in demand.

In an effort to clarify these predictions while at the same time representing an environment that might better approximate the limited substitutability between space and other consumption that characterizes an thoroughly built-up area like New York City, we consider a special case of the more general model considered in Brueckner (1987*a*).

Consider a "perfectly complementary" city where all households regard "space" and "other goods" as perfect complements. The utility function will be of the form: $u(\alpha, s, o) = min(\alpha \cdot s, o)$, where s represents the amount of space and o represents dollars spent on other goods.[17] In this model, s can be understood as either land or interior living space; the same intuition holds. α is a preference parameter with demand for "other goods" increasing in α and the demand for space decreasing as α increases. r is the land-rent function, which refers to the cost of land.

Households have income, m, and all households are employed in the central business district (CBD)

[16] Indeed, a common anecdote among those purchasing homes is that they purchase a bigger home, one with more bedrooms for example, because they have the ability to rent out that bedroom during peak seasons like holidays to help cover the cost of a mortgage.

[17] The qualitative comparative statics, e.g. the sign of changes to r_a, m, s, α, o, and N, do not depend on this particular utility function. Its simplicity makes it an attractive choice for a model. A more general case is presented in Brueckner (1987*b*).

which is located in the center of the city. As is customary, the CBD is regarded as a point in space. This implies that there are no differences in where a household is employed within the CBD. If a household is located x distance from the CBD, they must pay $t \cdot x$ annual commuting costs. Thus, a household will have $m - t \cdot x$ remaining to spend on space (s) and other goods (o). Consider distance and space to be measured in the similar units (e.g. meters and square meters).

Solving for the demand for s and o at distance x, we have:

$$o = \frac{(m - t \cdot x)\alpha}{\alpha + r} \tag{4}$$

Equation 4 implies that s is given by $\frac{m-t\cdot x}{\alpha+r}$, and o is given by $\frac{(m-t\cdot x)\alpha}{\alpha+r}$. Because $min(\alpha s, o) = u$ and $\alpha s = o$, we know that $\alpha s = u$, which implies that $s = \frac{u}{\alpha}$. Because a household can choose where to locate in the city and m is equal across the population , we know that every household with a given income, m, and α consumes the same amount of space. We can solve for rent as a function of utility and distance from the CBD.

Solving $\frac{m-t\cdot x}{r+\alpha} = \frac{u}{\alpha}$ for r, we obtain:

$$r = \frac{\alpha(m - t \cdot x - u)}{u} \tag{5}$$

Equation 5 presents the equilibrium land-rent function. At every point x (the distance to the CBD), r is determined by utility (u), income (m), transportation costs (t), and a preference parameter (α). As a natural component of spatial equilibrium, utility will be equal across all households and locations (otherwise households will move to maximize utility). This implies that property values fall as x (distance to the CBD) increases in order to equalize utility at every location. This must be the case because the farther away a household lives from the CBD, the more they spend on commuting costs (recall that commuting costs are equal to $t \cdot x$). Furthermore, in equilibrium all N households must be accommodated in the city, so property values must be sufficiently high in order to bid space away from alternative use.

With N total households, the total space bought by the households is $N\frac{u}{\alpha}$.[18] In a classical urban model,

[18] This model could be expanded to multiple classes, but the intuition and forthcoming results hold and so for simplicity, we will assume a one-class model. A multi-class model could take the form of different levels of income, m, or of the α preference parameter, modeled by a distribution of $f(M, \alpha)$.

r_a represents the agricultural price of land, but we can consider r_a to simply represent the opportunity cost, or alternative use value, of land. The total land "bid away" from this use is the land area where the price of space is greater than r_a. The radius of the city, $\overline{X}$, is determined when the value of land becomes equal to the value of space in alternative uses, so it is therefore the maximum distance from the CBD. The equilibrium requires that $N\frac{u}{\alpha}$ is equal to $\pi(\overline{X})^2$. This is the case because the (circular) city needs to accommodate the entire population and all space in the city will be consumed. If we set these two equal, we can solve for the equilibrium level of utility.

$$
\begin{aligned}
\overline{X} &= \frac{(-Nt \pm \sqrt{N}\sqrt{Nt^2 + 4m\pi(r_a + \alpha)})}{2\pi(r_a + \alpha)} \\
\overline{u} &= \frac{\alpha(Nt^2 + 2m\pi(r_a + \alpha) - \sqrt{N}t\sqrt{Nt^2 + 4m\pi(r_a + \alpha)})}{2\pi(r_a + \alpha)^2}
\end{aligned}
\tag{6}
$$

Because $\overline{X}$ must be positive (it is a distance), applying 6, the equilibrium land rent function is:

$$
\begin{aligned}
r &= -\frac{(-m + u + t \cdot x)\alpha}{u} \\
r &= \frac{2m\pi r_a(r_a + \alpha) + t(-Nt\alpha - 2\pi x(r_a + \alpha)^2 + \sqrt{N}\alpha\sqrt{Nt^2 + 4m\pi(r_a + \alpha)})}{Nt^2 + 2m\pi(r_a + \alpha) - \sqrt{N}t\sqrt{Nt^2 + 4m\pi(r_a + \alpha)}}
\end{aligned}
\tag{7}
$$

We can now look at the impact of three different exogenous variables that could change as the level of Airbnb activity increases, $N, \alpha,$ and m, on the land-rent function. These impacts are illustrated in Figures 2, 3, and 4. We can determine the impact of population by taking the derivative of the above land-rent function with respect to N.

$$
\frac{\partial r}{\partial N} = \frac{2\pi t(-m + t \cdot x)(r_a + \alpha)^2}{\left(\sqrt{N}\sqrt{Nt^2 + 4m\pi(r_a + \alpha)}\right)\left(-Nt^2 - 2m\pi(r_a + \alpha) + \sqrt{N}t\sqrt{Nt^2 + 4m\pi(r_a + \alpha)}\right)}
\tag{8}
$$

A rise in N is associated with an unambiguous increase in the value of space r at all distances x, and an increase in the slope of the rent gradient. The land-rent function must rise to bid away additional residential space from alternative uses in more remote parts of the city (e.g. the urban periphery). Equation 6 implies that the increase in N results in reduced utility $\overline{u}$, and therefore reduced consumption of space by each household and higher population density. Spatial equilibrium requires that the value of space per unit area decline by just enough to compensate for the extra transportation costs of households residing in that area.

Increasing density implies an increase in total transport costs per unit area, so increasing x requires more compensation – i.e. the land rent function must be steeper.

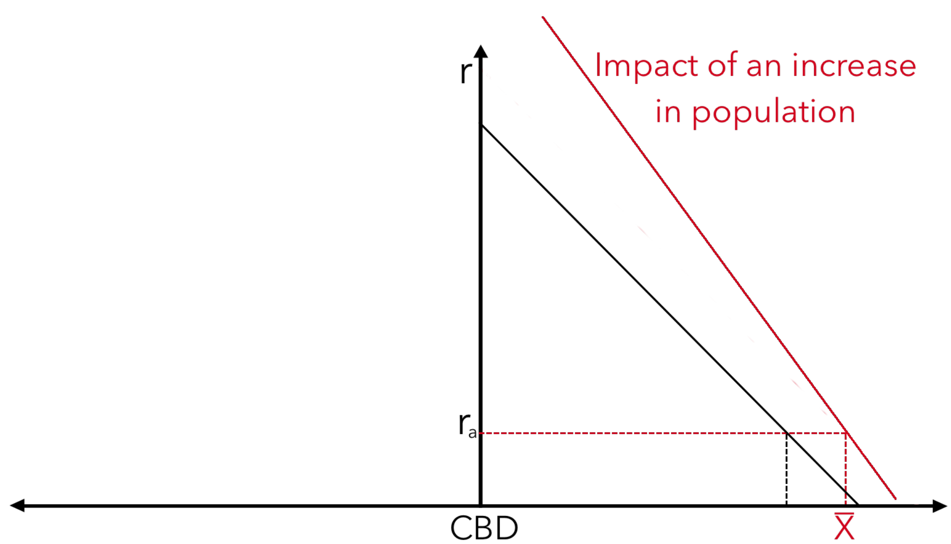
Why might the impact of Airbnb be modeled as an increase in N? In this simple model, N is fixed and exogenously determined. Airbnb listings allow more people (e.g. tourists) to occupy the city. For example, if a city experiences z private room listings, filled each night, the city has experienced an increase of z in N.

We can also determine the impact of income by taking the derivative of the land rent function with respect to m:

$$\frac{\partial r}{\partial m} = -\frac{2\pi t(r_a+\alpha)^2(2m\sqrt{N}\pi(r_a+\alpha)(nt+2\pi x(r_a+\alpha))(-\sqrt{N}t+\sqrt{Nt^2+4m\pi(r_a+\alpha)})}{\sqrt{Nt^2+4m\pi(r_a+\alpha)}(Nt^2+2m\pi(r_a+\alpha)-\sqrt{N}t\sqrt{Nt^2+4m\pi(r_a+\alpha)})^2)} \tag{9}$$

Airbnb presents homeowners with a new revenue stream. We can model this as a rise in income. With an increase in income, households will spend more both on space and other goods, and in the process experience an increase in $\overline{u}$. As a result, the city must expand. Because land consumption increases, density is reduced so the rent gradient will get flatter, implying that rents will fall in more central parts of the city and rise in more remote parts of the city. Figure 3 illustrates this effect.

Figure 2: Theoretical Impact of a Rise in Population



Finally, we can determine the impact of α by taking the derivative of the above land-rent function with

Figure 3: Theoretical Impact of a Rise in Income

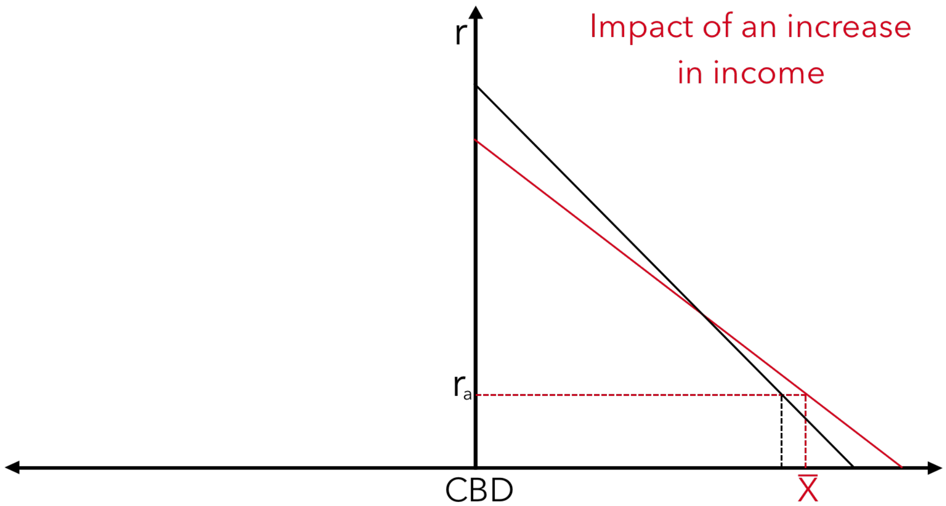
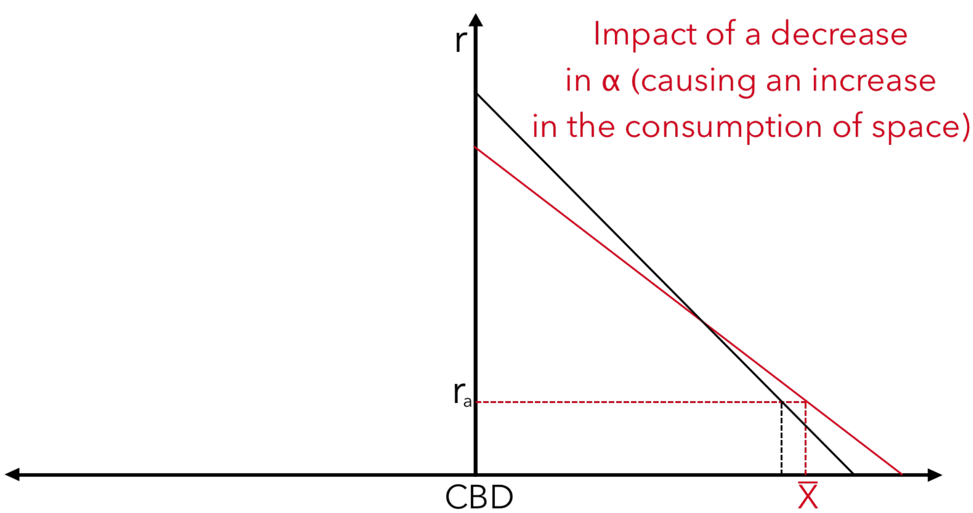


Figure 4: Theoretical Impact of a Decrease in α



respect to α, which gives:

$$\frac{\partial r}{\partial \alpha} = -\frac{t(-m\sqrt{N} + x(\sqrt{N}t + \sqrt{Nt^2 + 4m\pi(r_a + \alpha)})}{m\sqrt{Nt^2 + 4m\pi(r_a + \alpha)}} \tag{10}$$

An increase in α causes a decrease in the demand for space and vice versa. The impact we might expect as a result of Airbnb is a decrease in α, which would cause an increase in the consumption of space as residents purchased larger homes with seeking investment returns via short-term rentals. How does a decrease in α impact rent? Rent in the urban periphery, e.g. in more remote parts of the city, will rise by bidding away space from alternative uses to make available for residential housing consumption. The higher consumption of space will reduce density which in turn will reduce the slope of the rent function r (see Figure 4). As in the case of increasing income m, there would be a reduction in the cost of space in the city center and an increase at the periphery. Thus, the impact of changing α does not have a uniform impact.

If an increase in Airbnb activity in a city were equivalent to a rise in N we would therefore be justified in expecting an unambiguous rise in rent and property values, with a larger impact observed at more central locations. On the other hand, the theoretical impacts of α and m are ambiguous so that if an increase in Airbnb properties primarily affects the household demand for space or provides greater income there remains an empirical question to measure the actual impacts. This provides motivation for the empirical research presented below.

4 Data & Descriptive Statistics

Table 1 describes the different data sources used as well as their main uses. In total, there were eight main sources of data: 1) InsideAirbnb, 2) The Department of Finance Annualized Sales Data (January 2003-August 2015), 3) The Department of Finance "Places" or "Areas-of-Interest" Map, 4) Department of City Planning PLUTO$^{\text{TM}}$, 5) The 2010-2014 American Community Survey, 6) The New York Police Department Crime Statistics, 7) Census Geography Maps, and 8) the Metropolitan Transportation Authority Map of Subway Entrances.

Table 1: Data Sources and Use

Source	**Description** & **Use**
InsideAirbnb	InsideAirbnb (released by Murray Cox) contains information such as pricing, reviews, and location of each listing on Airbnb that was available on the date the Airbnb website was crawled (12 times in 2015-2016).
Department of Finance Annualized Sales Data: January 2003 - August 2015	The Department of Finance releases information on all sales in New York City. The data are available from 2003-2015 and contain information such as sale price, square footage,and sale date.
Department of Finance "Places" or "Areas-of-Interest" Map	The Department of Finance releases information on areas of interest, such as parks, cemeteries, and airports, available in GIS format.
Department of City Planning Pluto^{TM}	The Department of City Planning releases detailed information about each tax lot in New York City (of specific use for this analysis was square footage information).
American Community Survey 2010-2014	The American Community Survey contains information available at the Census Tract level such as education, racial and ethnic demographics, and employment-related measures.
New York Police Department Crime Statistics	The New York Police Department reports annual counts for different crimes (major felonies, non-major felonies, and misdemeanors) by precinct.
Census Geography Maps	In order to merge sales with local Census demographics, Census geographies needed to be identified and spatially joined to the sales dataset.
Metropolitan Transportation Authority Map of Subway Entrances	Information provided by the Metropolitan Transportation Authority was made into a map of subway entrances in New York City.

Table 2 and Table 3 document descriptive statistics for the variables used in this analysis. These data were aggregated and joined together using ArcGIS and Stata. Not all of these data are available at the same geographic scale. For example, crime statistics were only available to us at the geographic unit of precinct, which means that when controlling for crime for each sale, precinct is the level of granularity being used. In all, there were 1,252,891 observations (sales) from January 2003 through August 2015. We dropped 145,594 observations because they were non-residential sales, and 319,975 observations were dropped that had sales prices below $10,000,[19] We dropped 4,533 observations with sales prices above $10,000,000, and 2,552 observations were dropped because they were missing square footage information (or if square footage was below 10ft or above 50,000ft), leaving a total of 780,237 observations. Approximately 16,000 observations were excluded because they could not be properly geocoded.

For each of the remaining observed sales, we have information on sale price, sale date, square footage, and property type, along with some other variables in the Department of Finance Annualized Sales Data. Before describing how we are calculating Airbnb activity that could influence each sale, it is important to note the other information that was joined to the sales data. Most of the data, such as crime, Census information, distance to subway entrances and areas-of-interest, could be spatially joined using a combination of ArcGIS and Stata.

In the Department of Finance sales data, square footage was missing for approximately 50% of the observations. The size of the residential property is obviously an important variable for a hedonic regression or as a control for matching observations in a quasi-experimental approach. Rather than simply dropping half of the observations or excluding square footage as a variable, we employed a technique using the PLUTO™ dataset. PLUTO™ contains information on residential area (measured in square feet) and the number of residential units by Tax Lot and Block, both of which are very small geographic units of area. There are 857,458 Tax Lots with a mean of 1.254051 buildings per Lot. We calculated square footage by dividing residential living area by the number of residential units in each Lot and we were then able to join the sales data with this information to have a measure of square footage for an average unit in the same Lot as the sale.[20] While this method is not perfect, units in the same building and Lot tend to have

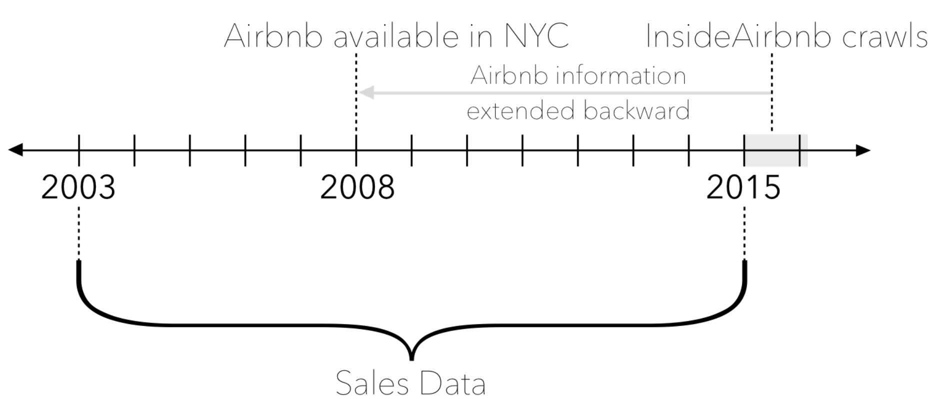
[19] Sales below $10,000 do not represent the actual sales prices of properties in New York City. Rather, they are either missing appropriate data or are bequests from one generation.

[20] For some sales, we were unable to join average square footage per Tax Lot. In these cases, we used average square footage per Tax Block.

roughly similar values and furthermore, where we had both square footage from the sales dataset and the calculated average square footage number from PLUTO^{TM}, the mean difference between these values for 379,673 observations was 41.68 square feet, which suggests that these measures are well within reasonable and expected levels of accuracy.

It is also worthwhile to review the Airbnb activity measures used to obtain the estimates presented in Section 5. InsideAirbnb scraped the Airbnb website to collect information on each listing available in New York City across several different crawl dates. Each crawl then presents a cross-section snapshot of data. Part of the information collected about each listing is the date of first review.[21] We take the date of first review to refer to one of the first, if not the first, booking that a listing receives. In other words, it can proxy for a given listing's entry into the New York City Airbnb marketplace. In order to construct a dataset from the 12 different InsideAirbnb datasets used, we merged the datasets from different crawls, keeping only distinct listings, and created an observation for each month the Airbnb unit was available using its date of first review as the first month of this time period. For instance, if a listing was available in the June 1st, 2015 crawl and its date of first review was June 1st, 2014, we conclude that it has been (at least potentially) active for the 12 corresponding months between the date of first review and crawl date. This process is visually represented in Figure 5.

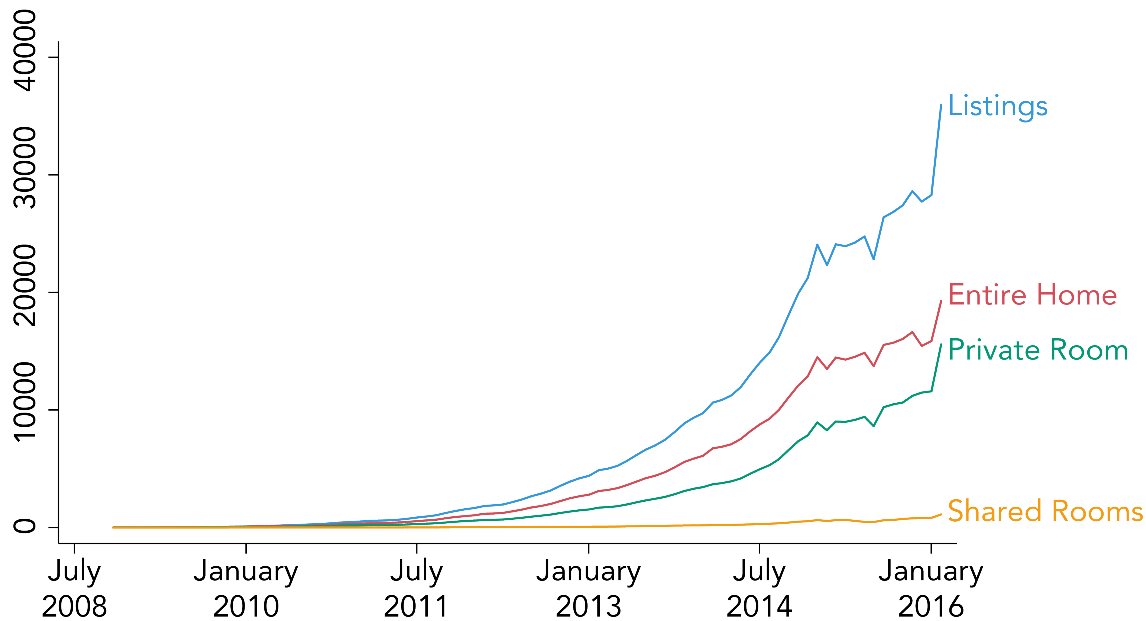
Figure 5: Construction of Airbnb Dataset



[21] In 2012, Brian Chesky, the founder and CEO of Airbnb, wrote on Quora that "72% of guests leave a review for hosts."

This allows us to get a clear picture of Airbnb activity going back to the appearance of the first listings when Airbnb entered the New York City market. In Figure 6, we include the number of listings over time generated through this process.

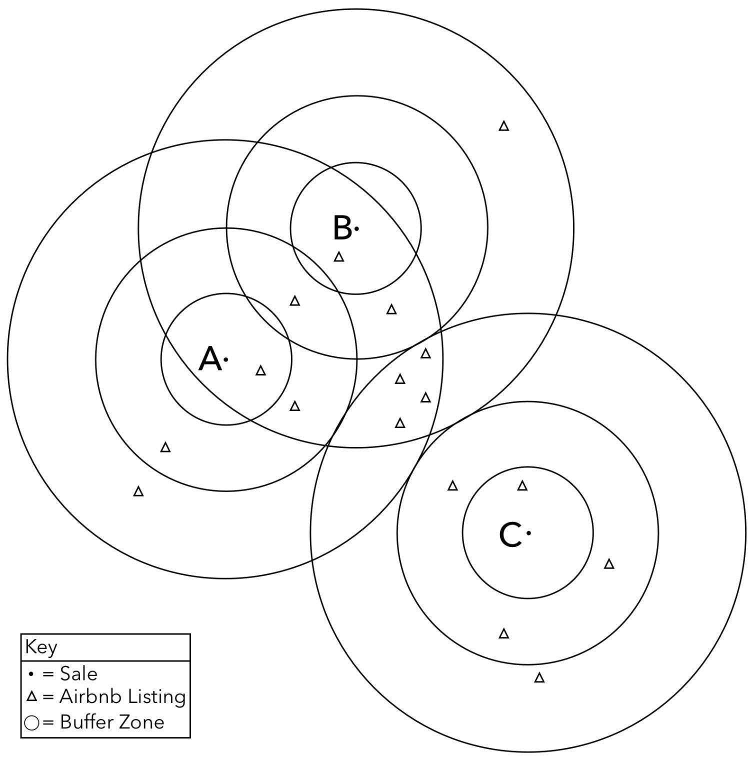
Figure 6: Airbnb Listings Over Time



There is the possibility of measurement error with this methodology because there are hosts who enter the Airbnb marketplace, e.g. create a listing, and then exit the market. As a result, these hosts and listings would not be captured in our analysis unless their listing was available during one of the crawls used for the analysis. In addition, there may be owners who make their property available on Airbnb very rarely, and our assumption that these units are available to influence local house prices may overstate the actual number of Airbnb properties. These sources of noise in measuring Airbnb units could result in attenuation bias, reducing the absolute value of the estimated impact of Airbnb units on property prices.

In order to evaluate the potential impact of Airbnb activity for each sale, we created five different buffer zones around every property sale in ArcGIS, with a radius of 150, 300, 500, 1000, and 2000 meters, respectively. This is visually represented in Figure 7. More specifically, in Figure 7, Sale A has 1 Airbnb listing within the first buffer zone, 4 Airbnb listings within the second buffer zone, and 11 Airbnb listings within the third buffer zone. It is worth noting that in this calculation, we are only looking at Airbnb listings available at the time of sale; we are able to do this because we extended Airbnb listings information back until entry of Airbnb into the New York market, as discussed above. In ArcGIS, we generated Airbnb activity measures for each sale in each of the five radii, such as number of listings, average price, and maximum capacity. These measures are documented in Table 2. In order to do so, in ArcGIS we had to select each sale, its corresponding Airbnb listings (available in the same month and year based on the Airbnb time series dataset created), perform a spatial join, and export this output to Excel to later read this into Stata for an econometric analysis. The code used for these data manipulations is available in Udell (2016).

Figure 7: Sales & Buffer Zones



Tables 2 and 3 include descriptive statistics; the first table details Airbnb activity measures and the second details information on each sale as well as other controls used.

In total, there are 780,237 observations with corresponding Airbnb activity.[22] As expected, the mean number of listings increases with the radius of the buffer zone. There are significantly more entire home and private room listings than there are shared room listings. There are two reasons why many entries in the Airbnb data are recorded as zero: 1) there are sales observations from 2003 through much of 2008, which is prior to Airbnb's entry into the market, 2) even after Airbnb became available, there are still many

[22]Because the number of observations is consistent across the entire table, it is not included.

Table 2: Descriptive Statistics: Airbnb Activity Measures

VARIABLES	(1) mean	(2) sd	(3) min	(4) max
Listing Counts, by Total and Type				
Listings Count (150m)	1.221	5.217	0	133
Listings Count (300m)	4.644	19.06	0	439
Listings Count (500m)	11.99	47.75	0	1,034
Listings Count (1000m)	40.99	157.5	0	2,899
Listings Count (2000m)	133.4	490.3	0	6,170
Entire Home Listings Count (150m)	0.855	3.821	0	101
Entire Home Listings Count (300m)	3.249	13.91	0	309
Private Room Listings Count (150m)	0.338	1.575	0	78
Private Room Listings Count (300m)	1.290	5.431	0	182
Shared Room Listings Count (150m)	0.0278	0.227	0	20
Shared Room Listings Count (300m)	0.104	0.577	0	35
Listing Capacity				
Avg. Capacity (150m)	0.423	1.147	0	16
Avg. Capacity (300m)	0.577	1.280	0	16
Max. Capacity (150m)	3.490	15.02	0	387
Max. Capacity (300m)	13.24	54.47	0	1,215
Avg. Bedrooms (150m)	0.158	0.430	0	10
Avg. Bedrooms (300m)	0.305	0.713	0	16
Sum Bedrooms (150m)	1.302	5.616	0	136
Sum Bedrooms (300m)	4.951	20.37	0	459
Sum Beds (150m)	1.819	7.841	0	294
Sum Beds (300m)	6.899	28.21	0	622
Listing Price				
Avg. Nightly Price (150m)	23.09	65.18	0	5,000
Avg. Nightly Price (300m)	29.34	69.00	0	5,000
Sum Price (150m)	213.744	989.79	0	25,308
Sum Price (300m)	813.8	3,617	0	74,874
Median Price (150m)	19.85	57.81	0	5,000
Median Price (300m)	24.69	60.49	0	5,000
Reviews				
Sum Reviews (150m)	31.77	140.4	0	4,396
Sum Reviews (300m)	122.0	499.6	0	11,5999

Table 3: Descriptive Statistics: Sales and Controls

VARIABLES	(1) mean	(2) sd	(3) min	(4) max	(5) N
Sales Unit					
Sale Price	683,922	913,580	10,000	1.000e+07	780,237
Square Footage of Unit	1,183	577.0	10.39	18,590	780,237
Walkup Building Indicator	0.0579	0.234	0	1	780,237
Presence of Elevator Indicator	0.368	0.482	0	1	780,237
Prewar Building Indicator	0.379	0.485	0	1	780,237
Demographics and Crime					
Median Household Income	75,240	35,874	11,012	250,001	776,027
Percentage White	0.549	0.300	0	1	779,975
Major Felonies	736.8	427.9	11	2,776	765,747
Non-Major Felonies	1,725	700.6	83	5,105	765,747
Misdemeanors	4,515	2,002	259	14,025	765,747
Geography and Time of Sales					
Indicator for Sale in Staten Island	0.0830	0.276	0	1	780,237
Indicator for Sale in Brooklyn	0.247	0.431	0	1	780,237
Indicator for Sale in the Bronx	0.0742	0.262	0	1	780,237
Indicator for Sale in Manhattan	0.283	0.450	0	1	780,237
Indicator for Sale in Queens	0.313	0.464	0	1	780,237
Year of Sale	2008	3.822	2003	2015	780,237

parts of New York City where Airbnb is not active. As shown in figure 6, Airbnb listings do not become a significant factor for the entire New York market until the beginning of 2010.

The different Airbnb measures represent different proxies for Airbnb activity.[23] It is worth noting here that the average nightly price within 300m of a sale is \$29.34. In many ways, Airbnb directly competes with hotels; the \$29.34 average price tag suggests that it also opens up a new market, which is a more affordable alternative to hotels. This is in line with Levin (2011), which suggests that these platforms have superior matching processes, creating a market for these transactions that otherwise might not have taken place. Airbnb represents an unbundling of the services hotels offer, which allows it to be cheaper in many cases.

In Table 3 we see that the average sale price is \$683,932 while the median sale price is \$450,000. 31.3% of sales occurred in Queens, 28.3% occurred in Manhattan, 24.7% occurred in Brooklyn, and the remaining 15.72% occurred in Staten Island and the Bronx.

[23]Most of these Airbnb measures proxy for levels of availability, but we can also think about a measure such as the sum of nightly prices as an indication of the potential (nightly) income available due to Airbnb activity.

The descriptive statistics presented in tables 2 and 3 allow us to make a quick "back of the envelope" calculation of the potential impact on property values. Consider the income capitalization approach outlined in section 3. Airbnb imposes a host fee of 3% of the rental value, in addition to the guest fees that are added to the nightly rental. It seems reasonable to expect that there will be many nights when the property is not rented, but suppose an optimistic owner of an average property expects to be able to rent 330 nights per year. Then the total annual Airbnb income expected would be $\$29.34 \times 330 \times 0.97 = \$9392$. Combining this figure with the mean property value of $683,922 this implies a value of $\alpha = 0.01373$ for equation 3.

For other variables in equation 3, we assume that $g = \gamma$ (the expected capital gain equals the ownership risk premium) and apply reasonable estimates to other variables as follows:

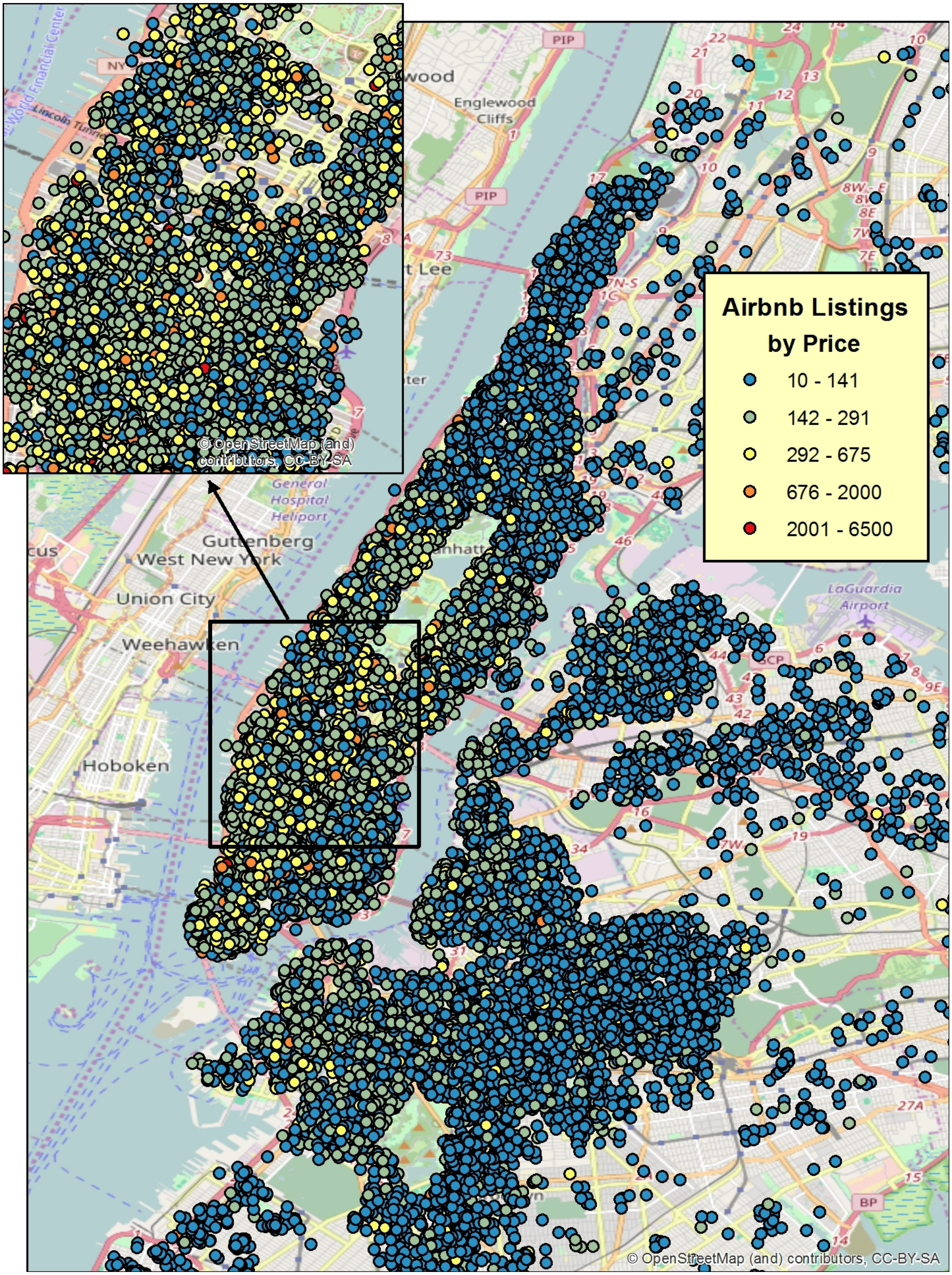
Variable	**Value**	**Interpretation**
r_{rf}	0.02	Risk free annual interest rate
ω	0.025	Property tax rate as a percent of market price
τ	0.29	Effective tax rate on personal income
r_{m}	0.04	Annual mortgage interest rate
δ	0.025	Maintenance costs as a percent of market price
α	0.01373	Airbnb rental as a percent of market price

Using these values in both equations 2 and 3, we can calculate that the availability of Airbnb rentals has diminished the user cost of housing by about 17.7%. If utility levels in the city remain constant (as would be expected in long-run equilibrium of an open city), and given unchanged transport costs and preferences, we would expect rents per unit of space to remain unchanged. This reduction in the user cost of housing would then imply, via equation 1 a **17.7% increase in the price of housing**.

These calculations are at best an approximation of what we might expect to observe. Not all portions of the city are equally exposed to Airbnb activity and market equilibrium may take years to be realized. Nevertheless, the calculation provides some intuition about the potential magnitude of price impacts.

Not all portions of the city have the same intensity of Airbnb listings. Figure 8 shows the distribution of Airbnb listings (from any time period) across the city, with dots color coded by daily price. It can be difficult from the map to tell how dense the coverage is, so an inset showing midtown Manhattan is provided. This suggests that as of late 2015, coverage in the areas of the city with greatest demand for lodging is very complete.

Figure 8: Airbnb listings in New York City, with inset showing midtown Manhattan



5 Empirical Estimates

We employ two distinct approaches to estimating the impacts of Airbnb properties on house prices. First, we employ a relatively traditional hedonic approach as presented and explained in Rosen (1974) or Sheppard (1999) and widely used to measure the importance of factors affecting property values. Second, we employ several quasi-experimental approaches to identify *treatment* and *control* groups within the observational data, and then estimate the average treatment effect generated by the Airbnb quasi-experiment.

The first approach provides a measure of the associational impact of Airbnb – the change in values that an observant buyer might detect as the housing market adapts and responds. It cannot, however, pretend to provide an analog to the causal impact obtained from a controlled experiment in which the sales price of identical (or very similar) structures are compared after one of them (the treated property) is subject to the impact of locally available Airbnb rentals while the other (the control) is not subject to these local impacts.

Because we are fortunate to have a very large number of individual sales observations, we can apply these techniques to identify the experimental data within the large observational data. This offers the prospect of measuring a causal impact, and it is worth distinguishing between this approach and the use of instrumental variables that are widely applied in response to concerns about endogenous variables. Instrumental variable approaches can (in ideal circumstances) reduce endogeneity bias in estimating associational relations, but cannot be relied upon to measure causal impacts.

Our unit of observation is an individual sale that took place in New York City (five boroughs) between January 2003 and August 2015. We therefore have a large number of sales both before and after Airbnb units become actively available.[24] For each sale, we include controls for the property itself, the building in which it is located, local amenities (such as access to public transportation), local neighborhood characteristics (demographics and crime), a year of sale fixed effect to capture a time trend of sales prices, and a local neighborhood fixed effect to capture time invariant neighborhood quality or desirability. For each sale, we calculate a level of local Airbnb activity, which is the main variable of interest, and corresponds to Airbnb activity at the time of sale. In most specifications, this Airbnb activity is proxied by the number of listings,

[24] It is worth noting that the sales are nominal rather than real prices. we include year of sale fixed effects to deal with this problem. This is, in fact, preferable to using a house price index to determine "real prices" because available house price indices generally cover a different geographic area than our data.

We compare the index, which is constructed from the estimates on the year of sale fixed effects, to the S&P/Case-Shiller NY, NY Home Price Index to demonstrate its plausibility.

but we present estimates that use alternative indices of Airbnb activity as well.

There are two main assumptions of the hedonic identification strategy: 1) with regards to generating the Airbnb dataset, we are assuming that the date of first review indicates when a property became available on Airbnb and that once it became available, it never exited the Airbnb market. This allows us to construct a dataset of Airbnb activity over time and calculate local Airbnb activity at the time of sale and 2) local neighborhood fixed effects capture time-invariant local neighborhood quality. If these assumptions are valid, these estimates will reveal the impact of local Airbnb activity on sales prices. If these assumptions hold, because we are controlling for property, building, and neighborhood characteristics, the only thing that is changing is local Airbnb activity (as well as the overall level of the market, which is captured by year of sale fixed effects).

The specification we are using in the baseline model follows the form:

$$\begin{aligned} ln(\text{Sale Price}_{icmt}) = \alpha + \beta_1 ln(\text{Airbnb Activity}_{im}) + \mu_1(\text{Property Characteristics}_i) + \\ \mu_2(\text{Building Controls}_i) + \mu_3(\text{Demographic and Crime Controls}_{it}) + \\ \mu_4(\text{Year of Sale FE}_{it}) + \mu_5(\text{Local Neighborhood FE}_{ic}) + \epsilon_{icmt} \end{aligned} \tag{11}$$

where $ln(\text{Sale Price}_{icmt})$ is equal to the logarithm of property i's sale price, in neighborhood c, in month m, and year t, and where β represents a scalar coefficient and μ represents a vector coefficient.

The independent variable is the natural log of sale price. The main variable of interest is Airbnb activity (proxied by different descriptive and proximate measures of Airbnb, as will be discussed in Section 5). For each sale, square footage, distance to the nearest subway entrance and area of interest are used as well as controls for the building, year of sale, local crime, and local demographics. In the model, a time-invariant local neighborhood fixed effect is included to capture unobservable or uncontrolled for local neighborhood quality and characteristics. There is significant evidence that housing prices are heavily influenced by the characteristics of a neighborhood as well as surrounding land use (DiPasquale & Wheaton 1996, p. 349).

As with most microeconometric estimation, there are natural concerns regarding endogeneity of right-hand side variables. We are not estimating the individual household demand for the characteristic of proximity to Airbnb properties or for listing a property on Airbnb, so the traditional concerns regarding endogeneity of individual household decisions discussed in Sheppard (1999) do not arise. Endogeneity may nevertheless be a valid concern if important factors affecting house prices are correlated with the unobserved errors in the hedonic equation. Thus, for example, if errors ϵ in the hedonic price function are correlated with measured values of right-hand side variables in equation 11 then estimates may be biased.

For example, we might expect increasing Airbnb activity to be correlated with the error term of the hedonic if the number of Airbnb properties within a given buffer distance were positively related to unobserved errors ϵ. Note that the problem does not involve a correlation between Airbnb activity and property values. The problem arises if we have correlation between Airbnb activity and ϵ, which is the component of property value that is **not explained** by the hedonic.

Proving there is no such relationship is extremely difficult. There are several considerations that we suggest as a basis for regarding our hedonic estimates as reasonable: 1) we include sales data prior to Airbnb's entry into the New York City market and therefore have at least five years of data (2003 through most of 2008), where sales are not subject to any Airbnb "treatment,"[25] 2) local neighborhood fixed effects, which in our preferred specification are at the level of Census Block-Group, and 3) use of robust standard errors, which in our preferred specification are clustered at the level of Census Tract, to help deal with correlation within clusters and heteroskedasticity. Finally, even if we expected there to be correlation between unexplained errors ϵ in the hedonic model and the number of Airbnb properties very near to the source of error, this correlation should be greatly reduced as we consider larger buffer areas. A distance exceeding 1,000 meters in the New York housing market is generally large enough to be associated with significant neighborhood change. As noted in section 4, these larger buffer areas also involve many more properties, and it strains credulity that the number of Airbnb properties within a kilometer in any direction would be significantly affected by an unusually under- or over-valued property sale.

While this approach is not immune from endogeneity concerns and makes other implicit assumptions concerning stability of trends, the central role of the treatment variable interacted with the indicator for the time period after which any treatment is delivered, coupled with the reduced likelihood that this interaction variable is correlated with the unobserved ϵ in the model make presentation of these estimates worthwhile. A final check is provided by comparing the estimates of the "preferred" models from each approach with the intuitive "back of the envelope" calculations presented in section 4 will be instructive as indicators of the reasonableness of the estimates.

[25]Therefore, the change we are identifying, controlling for property and local neighborhood characteristics as well as the overall level of the market, should be attributable solely to Airbnb activity.

5.1 Estimating Associative Effects with Hedonic Models

Table 4 presents OLS estimates of the hedonic using several different measures of Airbnb activity, all measured within 300 meter buffers. This is followed by Table 5, which shows results for counts of Airbnb properties measured within buffers of different sizes. The results of Table 5 are then summarized graphically in Figure 9.

Note in tables 4 and 5 that the variables providing a measure of Airbnb activity are always positive and statistically significant. A doubling (100% increase) in the number of Total Airbnb accommodations is associated with a 6.46% increase in property values. Other variables always have the expected signs and are mostly statistically significant.

From table 5 we note that moving to larger buffers does reduce the magnitude of the estimate, but all are positive, significant and a doubling of Airbnb activity is associated with an increase of property values of between 6% and nearly 11%.

While this is a smaller impact than suggested by the "back-of-the-envelope" calculation presented above, it is encouraging to note that these results are almost identical to those obtained by Barron et al. (2017), who find associative impacts of between 3% and 35% on house price indices with 7% in their most completely specified models.

Using the estimated parameters associated with each year in model (1) of table 4 as the basis for constructing a house price index, we can compare the constructed index with the Case-Shiller-Weiss index for New York City over the same period. The results are illustrated in figure 10. While we would not expect the two indices to be identical, the close correspondence over the relevant time period encourages our confidence in the hedonic models.

Table 4: OLS estimates of Airbnb impacts

Variables	(1) ln(Sale Price)	(2) ln(Sale Price)	(3) ln(Sale Price)	(4) ln(Sale Price)
Total Accommodations	0.0646***			
	0.00275			
Total Reviews		0.0393***		
		0.00173		
Total Rooms			0.0814***	
			0.00351	
Total Rents				0.0323***
				0.00133
Square Feet	0.402***	0.402***	0.402***	0.402***
	0.0178	0.0178	0.0178	0.0178
Felonies	-0.0458***	-0.0552***	-0.0455***	-0.0517***
	0.0161	0.0162	0.0162	0.0161
Pre-war	0.0843***	0.0846***	0.0842***	0.0847***
	0.0111	0.0111	0.0111	0.0111
Distance to AOI	-0.103	-0.101	-0.103	-0.102
	0.0674	0.0674	0.0675	0.0674
Distance to subway	-0.00875	-0.00880	-0.00897	-0.00897
	0.0243	0.0241	0.0243	0.0242
Elevator	0.0858***	0.0849***	0.0863***	0.0847***
	0.0235	0.0235	0.0235	0.0234
Y_{2004}	0.179***	0.180***	0.178***	0.180***
	0.0121	0.0119	0.0121	0.0120
Y_{2005}	0.365***	0.367***	0.365***	0.366***
	0.0127	0.0126	0.0128	0.0126
Y_{2006}	0.464***	0.467***	0.464***	0.466***
	0.0164	0.0159	0.0164	0.0161

**** - significant at 1%, ** - significant at 5%, * - significant at 10%*

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Variables	(1) ln(Sale Price)	(2) ln(Sale Price)	(3) ln(Sale Price)	(4) ln(Sale Price)
Y_{2007}	0.490***	0.492***	0.490***	0.491***
	0.0179	0.0175	0.0179	0.0177
Y_{2008}	0.465***	0.467***	0.465***	0.466***
	0.0192	0.0188	0.0192	0.0190
Y_{2009}	0.341***	0.338***	0.343***	0.339***
	0.0171	0.0178	0.0170	0.0174
Y_{2010}	0.352***	0.345***	0.356***	0.344***
	0.0184	0.0182	0.0185	0.0181
Y_{2011}	0.311***	0.297***	0.318***	0.296***
	0.0160	0.0165	0.0161	0.0160
Y_{2012}	0.344***	0.336***	0.351***	0.333***
	0.0157	0.0150	0.0160	0.0152
Y_{2013}	0.325***	0.323***	0.331***	0.318***
	0.0143	0.0132	0.0146	0.0137
Y_{2014}	0.389***	0.401***	0.394***	0.391***
	0.0138	0.0125	0.0140	0.0132
Y_{2015}	0.432***	0.455***	0.436***	0.437***
	0.0151	0.0137	0.0152	0.0143
Constant	10.84***	10.88***	10.84***	10.87***
	0.490	0.498	0.490	0.494
Observations	765,747	765,747	765,747	765,747
R-squared	0.524	0.524	0.524	0.524
Sale-Year FE	YES	YES	YES	YES
Local Neighborhood FE	Census Block Group	Census Block Group	Census Block Group	Census Block Group
Clustered Standard Errors	Census Tract	Census Tract	Census Tract	Census Tract

**** - significant at 1%, ** - significant at 5%, * - significant at 10%*

Table 5: OLS estimates of Airbnb impacts with increasing buffer sizes

Variables	(1) ln(Sale Price)	(2) ln(Sale Price)	(3) ln(Sale Price)	(4) ln(Sale Price)	(5) ln(Sale Price)
Airbnb$_{150}$	0.109***				
	0.00555				
Airbnb$_{300}$		0.0879***			
		0.00377			
Airbnb$_{500}$			0.0773***		
			0.00309		
Airbnb$_{1000}$				0.0670***	
				0.00261	
Airbnb$_{2000}$					0.0601***
					0.00249
Sauare Feet	0.403***	0.403***	0.403***	0.402***	0.402***
	0.0180	0.0179	0.0179	0.0179	0.0179
Felonies	-0.0574***	-0.0363**	-0.0268*	-0.0243	-0.0307*
	0.0171	0.0161	0.0159	0.0156	0.0158
Pre-war	0.0838***	0.0838***	0.0839***	0.0842***	0.0840***
	0.0112	0.0112	0.0112	0.0112	0.0112
Distance to AOI	-0.0993	-0.100	-0.100	-0.0997	-0.0991
	0.0770	0.0770	0.0768	0.0772	0.0770
Distance to subway	-0.00978	-0.00931	-0.00984	-0.0111	-0.0113
	0.0251	0.0250	0.0249	0.0249	0.0248
Elevator	0.0904***	0.0907***	0.0907***	0.0903***	0.0902***
	0.0239	0.0239	0.0239	0.0238	0.0238
Y_{2004}	0.180***	0.177***	0.176***	0.175***	0.176***
	0.0122	0.0121	0.0119	0.0118	0.0116
Y_{2005}	0.366***	0.363***	0.362***	0.362***	0.363***
	0.0129	0.0127	0.0125	0.0123	0.0122

**** - significant at 1%, ** - significant at 5%, * - significant at 10%*

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Variables	(1) ln(Sale Price)	(2) ln(Sale Price)	(3) ln(Sale Price)	(4) ln(Sale Price)	(5) ln(Sale Price)
Y_{2006}	0.465***	0.462***	0.461***	0.461***	0.462***
	0.0168	0.0164	0.0161	0.0159	0.0157
Y_{2007}	0.490***	0.488***	0.488***	0.488***	0.489***
	0.0181	0.0180	0.0177	0.0176	0.0175
Y_{2008}	0.465***	0.464***	0.463***	0.464***	0.465***
	0.0194	0.0193	0.0191	0.0190	0.0189
Y_{2009}	0.345***	0.341***	0.338***	0.330***	0.316***
	0.0168	0.0171	0.0171	0.0170	0.0168
Y_{2010}	0.360***	0.354***	0.346***	0.331***	0.313***
	0.0185	0.0185	0.0184	0.0180	0.0174
Y_{2011}	0.328***	0.307***	0.286***	0.255***	0.219***
	0.0156	0.0159	0.0160	0.0155	0.0148
Y_{2012}	0.359***	0.327***	0.303***	0.269***	0.228***
	0.0161	0.0159	0.0152	0.0145	0.0135
Y_{2013}	0.364***	0.328***	0.302***	0.265***	0.220***
	0.0150	0.0147	0.0142	0.0136	0.0129
Y_{2014}	0.421***	0.385***	0.357***	0.317***	0.269***
	0.0144	0.0142	0.0137	0.0132	0.0128
Y_{2015}	0.467***	0.428***	0.398***	0.355***	0.308***
	0.0156	0.0155	0.0149	0.0148	0.0147
Constant	10.88***	10.75***	10.70***	10.69***	10.73***
	0.545	0.547	0.548	0.552	0.553
Observations	742,328	742,328	742,328	742,328	742,328
R-squared	0.524	0.524	0.525	0.525	0.525
Local Neighborhood FE	Census Block Group	Census Block Group	Census Block Group	Census Block Group	Census Block Group
Clustered Standard Errors	Census Tract	Census Tract	Census Tract	Census Tract	Census Tract

**** - significant at 1%, ** - significant at 5%, * - significant at 10%*

Figure 9: Airbnb impacts for different buffer sizes

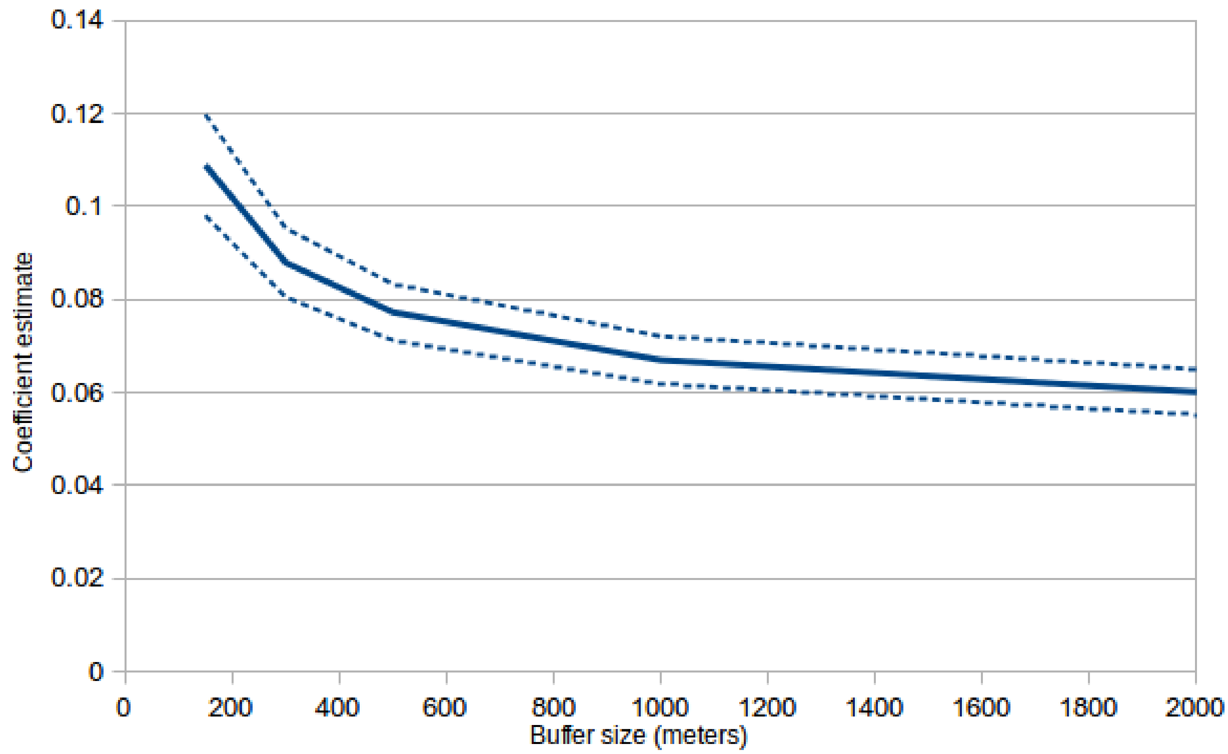
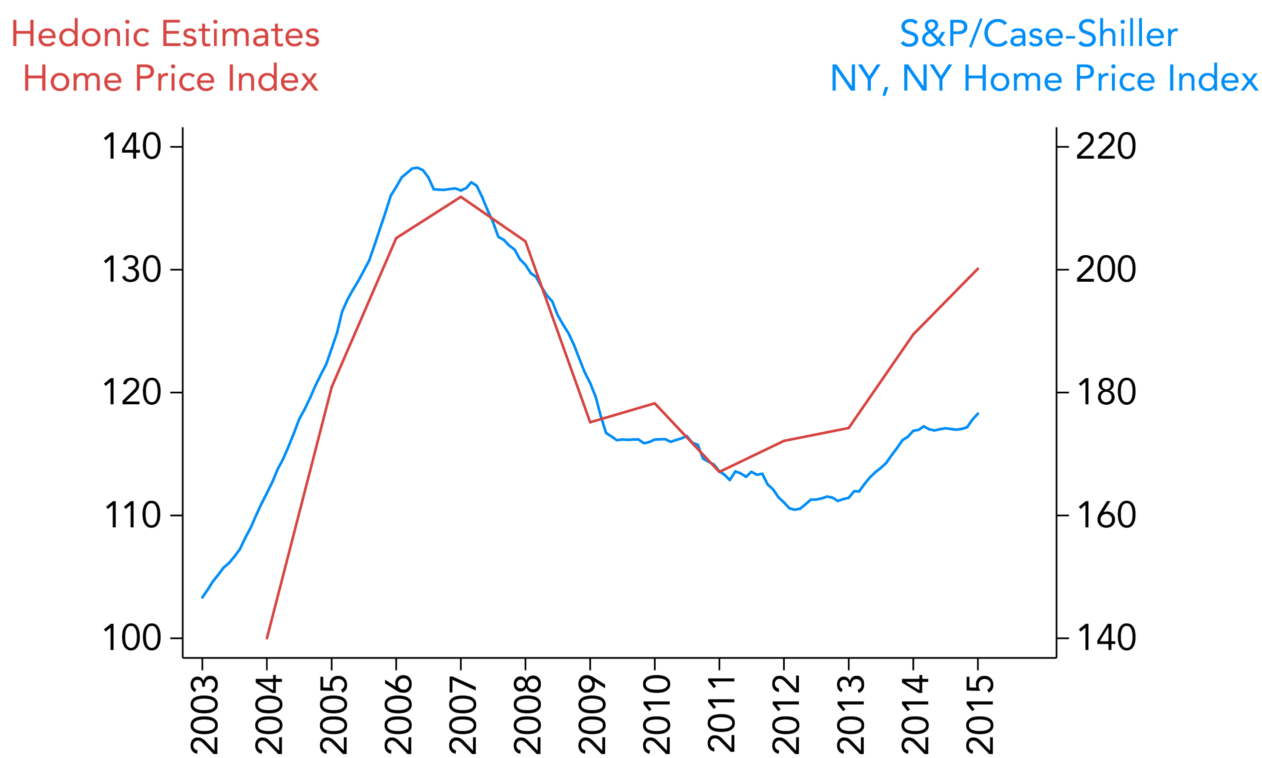


Figure 10: Comparison of house price index from Airbnb model with CSW index



5.2 Quasi-Experimental Estimation of Airbnb Treatment Effects

The results presented in the preceding subsection cannot be given a clear causal interpretation. Hedonic models present the association observed in equilibrium between structure and neighborhood characteristics (such as the presence of Airbnb properties within 300 meters of the property) and the recorded sale price. As noted in Sheppard (1999) the hedonic price function arises from the interaction of supply and consumption choices made in the housing market and describes a locus of equilibrium outcomes rather than a behavioral or causal link.

To properly evaluate the causal impact of Airbnb properties on house prices, we would ideally have a controlled experiment in which identical properties were identified, one of them exposed to the treatment of having nearby Airbnb properties and one of them insulated from this treatment, and the sales prices could then be compared over a sample of properties to estimate the impact on house prices caused by Airbnb.

The impracticality of conducting such an experiment is obvious, but our observational data permit application of widely-used[26] quasi-experimental approaches. These approaches permit us, given certain assumptions, to identify the experimental information that are contained within our observational data and to approximate a controlled experimental design. The large size and extensive time over which our data are observed make this a particularly appropriate methodology for application.

We employ three methods for evaluating treatment effects: construction of treatment and control groups based on nearest-neighbor matching, based on propensity-score matching, and the use of regression adjustment for determination of treatment and control groups.

Table 6 provides the estimated treatment effects, based on sales prices adjusted for prevailing property price levels using the Case-Shiller-Weiss house price index for New York City. Note that 'treatment' here means that the sale of a residential property took place at a time when there were Airbnb properties available within 300 meters of the sale property location. The first rows present estimates making use of all properties with full data in the sample, without regard to location. Subsequent rows, as noted in the first column, break the data into subsamples based on the distance between the sale property and the CBD, here taken to be Wall Street in lower Manhattan.

The first column of average treatment effect estimates is obtained using nearest-neighbor matched pairs

[26]See discussion and references in Chapter 21 of Wooldridge (2010) or Chapters 1 and 2 of Cerulli (2015).

based on the Mahalanobis distance between observations, applying large-sample bias correction. Beneath estimate of treatment effects is the estimated standard error. The second column presents estimates of average treatment effects constructing treatment and control groups using propensity score matching. The third column presents estimated average treatment effects using regression adjustment, followed by the mean potential outcome for the data and the number of observations.

In every case, the estimated standard errors are very small so that estimated precision of the estimates is high. Estimated treatment effects on the population are generally somewhat higher than the associational estimates obtained using the hedonic models or our 'back-of-the-envelope' calculations, ranging from a nearly 21% impact estimated using nearest-neighbor comparisons to nearly 35% using regression adjustment.

Table 6: Estimated effect of treatment: presence of Airbnb property within 300 meters

	Nearest Neighbor	Propensity Score	Regression Adjustment	Mean Potential Outcome	Observations
All distances	0.2094***	0.3171***	0.3493***	13.0494***	710,422
σ	0.007	0.006	0.003	0.001	
Less than 7 km	0.3252***	0.5142***	0.5490***	13.1592***	171,815
σ	0.058	0.014	0.005	0.004	
7 km to 11.5 km	0.2405***	0.3113***	0.2854***	13.2848***	189,492
σ	0.057	0.008	0.005	0.002	
11.5 km to 17 km	0.1734***	0.2774***	0.1678***	12.8657***	166,121
σ	0.020	0.011	0.007	0.002	
More than 17 km	0.1051***	0.0490***	0.0428***	12.9035***	182,994
σ	0.024	0.014	0.010	0.002	

**** - significant at 1 percent*

Our data include an extended time period during which there were no treated properties. The very first treated sales occur in 2008 but, as noted above and illustrated in Figure 6, most treated sales take place after the beginning of 2010. Even in 2012 the majority of property sales are not within 300 meters of a property ever available on Airbnb and hence 'untreated'.

For all estimation approaches, we see that the average treatment effects are higher for properties located closer to the commercial center, and lower for those properties located further away. This is not simply an artifact of more intense treatment (in the sense of proximity to more Airbnb properties) for more centrally located sales. Table 7 presents a set of estimated treatment effects for the population that distinguishes between different intensities of treatment.

As expected, we see that for all distances (the first column of estimates) the treatment effect rises with intensity of treatment. Properties sold within 300 meters of 1 to 5 Airbnb properties sell for about 16% more, while those exposed to 31 or more properties sell for a 77% premium. This general pattern holds within distance bands as well. Average treatment effects rise with treatment intensity for properties within 7 kilometers of the center as well as for those further out. In addition, restricting attention to a particular treatment intensity and moving along the row (to more distant properties) shows again that the treatment effect tends to decline. Thus, for example, a property exposed to between 6 and 10 Airbnb properties sells for a 58% premium within 7 km of the center, and the treatment effect diminishes as we consider properties further from the center (but exposed to the same intensity of treatment).

Figure 11 illustrates these results. The diagram shows a dot for each value in Table 7, and we see that within each color group (distance from the center) the estimated treatment effect rises with the intensity of treatment. We also see that, in general, the red dots (closest to CBD) are higher than the blue, which in turn are higher than the green. This indicates that the increase in house prices (and presumably the price of space) is greater at central locations and diminishes as we move towards the periphery of the city.

Table 7: Estimated effect of different treatment levels

# Airbnb	All Distances	Less than 7km	7km to 11.5km	11.5km to 17km	More than 17km
1 to 5	0.1596***	0.1413***	0.1653***	0.0855***	0.0354 ***
σ	0.004	0.010	0.006	0.007	0.011
6 to 10	0.4553***	0.5838***	0.3371***	0.2202***	-0.0522
σ	0.012	0.010	0.012	0.046	0.125
11 to 15	0.5399***	0.6486***	0.4228***	-0.1171	
σ	0.030	0.012	0.019	0.194	
16 to 20	0.6636***	0.6712***	0.4999***	0.4179*	
σ	0.035	0.014	0.023	0.241	
21 to 25	0.6403***	0.6699***	0.5361***	-0.0761	
σ	0.037	0.015	0.027	0.237	
26 to 30	0.6436***	0.6499***	0.5379***	-0.3063	
σ	0.043	0.019	0.034	0.365	
31 or more	0.7748***	0.7934***	0.5903***	-0.0325	
σ	0.018	0.007	0.016	0.173	

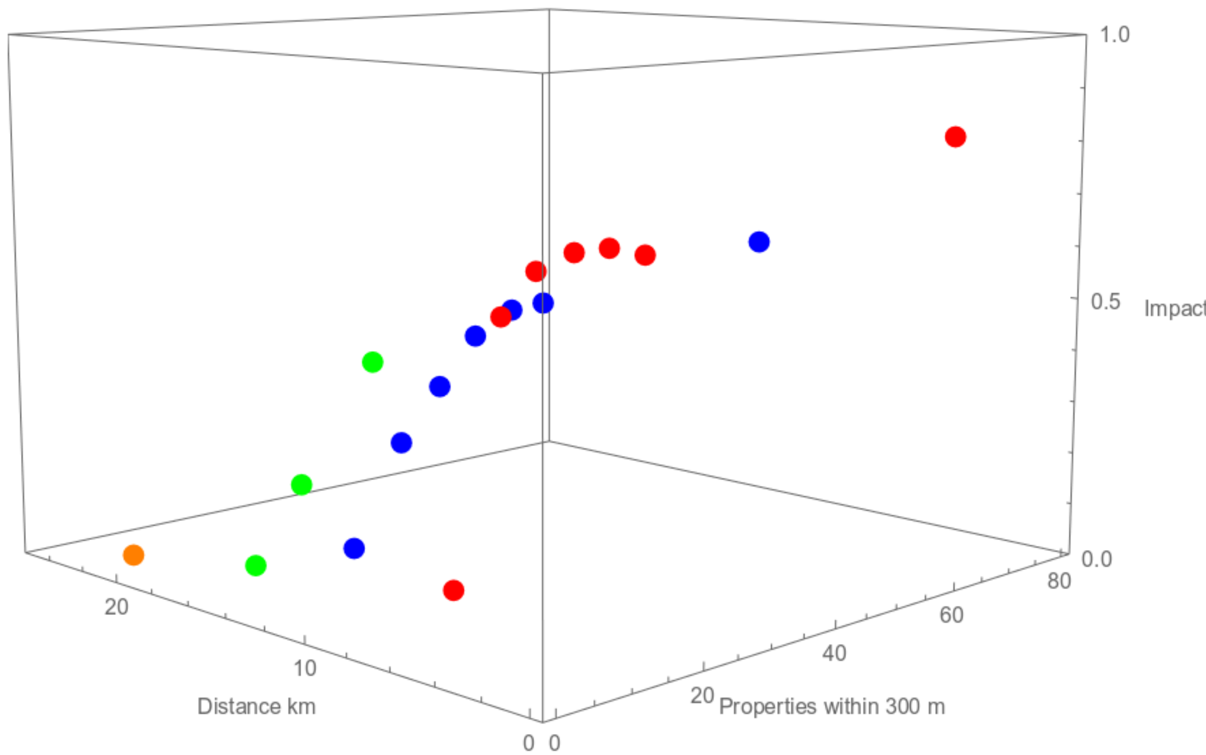
**** - significant at 1 percent, * - significant at 10 percent*

Table 8: Estimation with endogenous treatment effects

Sales price (outcome)	All Distances	Less than 7 km	7 to 11.5 km	11.5 to 17 km	More than 17 km
Treatment	0.6456***	1.3613	1.0088***	0.3840***	-0.0481
σ	0.114	1.449	0.119	0.125	0.080
Square feet area	0.6556***	1.0315***	0.5689***	0.4784***	0.5623***
σ	0.126	0.297	0.078	0.053	0.029
Felonies	-0.0486	-0.0809	-0.0821	0.0249	-0.0405
σ	0.050	0.136	0.051	0.050	0.053
Median income	0.1746*	0.0633	0.3363***	-0.0298	0.0611
σ	0.101	0.161	0.065	0.053	0.052
Percent white	0.0201	0.0647	0.0295	-0.0398*	0.0290***
σ	0.013	0.112	0.023	0.021	0.010
Pre-war construction	0.2222***	0.3852**	0.1551***	0.2685***	0.1770***
σ	0.050	0.169	0.028	0.028	0.035
Wall St. Distance	-0.2505***	-0.2195	-0.3766**	-0.2661	-0.1381
σ	0.039	0.136	0.178	0.215	0.134
Elevator	0.1905**	0.6893**	0.2473***	0.1018	-0.0938*
σ	0.085	0.304	0.089	0.063	0.054
Constant	7.2420***	5.5297***	6.6094***	10.1850***	8.9606***
σ	0.897	1.561	1.396	1.153	0.861
Treatment model					
Columbus Cir Distance	-0.0674***	0.0311	-0.0631***	-0.0797***	-0.0429***
σ	0.008	0.045	0.009	0.014	0.012
Distance to AOI	0.00010**	-0.00001	0.00009	0.00016**	-0.00009
σ	0.00004	0.00005	0.00005	0.00007	0.00006
Distance to subway	-0.00024***	-0.00008	-0.00029***	-0.00016**	-0.00016***
σ	0.00004	0.00024	0.00008	0.00006	0.00004
Constant	-0.1927	-0.5146	-0.1751	-0.2977	-0.6097**
σ	0.143	0.366	0.145	0.235	0.294
ρ	-0.1572*	-0.4655	-0.4914***	-0.1188***	0.0621
	0.1199	0.5960	0.0684	0.0626	0.0388
σ	0.8511	1.0979	0.8621	0.7264	0.6595
	0.0700	0.3650	0.0255	0.0248	0.0235
λ	-0.1338**	-0.5111	-0.4237***	-0.0863***	0.0409*
	0.0930	0.8240	0.0679	0.0467	0.0258
$\chi^2(1)$	1.66	0.44	35.62***	3.53*	2.55
P[ ] $> \chi^2$	0.1976	0.5074	0	0.0602	0.1104
Observations	710422	171815	189492	166121	182994
Nbd clusters	494	157	186	260	222
$\chi^2(8)$	493.13***	150.27***	669.5***	222.72***	618.7***

**** - significant at 1 percent, ** - significant at 5 percent, * - significant at 10 percent*

Figure 11: Impact on house prices of different treatment levels at various distances



There is a natural concern that these results may be an artifact of some endogeneity in the treatment of properties. This is not a fully randomized assignment of treatment to similar properties, and it may be that (despite the results presented in Table 7) some element of high-demand locations might be subjecting properties closer to the CBD to more intense treatment. We consider the possibility that these impacts may be distorted by endogeneity of treatment, and present the resulting estimates in Table 8.

As expected, the more demanding estimation approach results in somewhat less precise estimates, but overall the results are quite comparable to those presented in the previous tables. The treatment model considers three measures of location advantage to identify areas where treatment is more likely. Distance from Columbus Circle, distance to other areas of interest identified by the Department of Finance, and distance to the nearest subway station. Only distance to Columbus Circle and to the nearest subway station are typically estimated with precision. The models cluster standard errors by neighborhood.

Overall, the results suggest average treatment effects that are larger in the central locations and diminish (to the point of insignificance) as we move towards the periphery of the city. For all distances combined, the average treatment effect indicates a 64% premium for treated sales taking place within 300 meters of other properties that are available via Airbnb.

Interestingly, the estimated correlation ρ is negative, indicating that unobservable factors that increase property sales prices tend to occur with unobservables that decrease the chance of nearby Airbnb properties. This increases our confidence that the estimated average treatment effects are not merely an artifact of endogenous treatment probabilities, even in those distance bands where the chi-square test indicates that we must reject the hypothesis of no endogeneity in treatment selection.

6 Conclusions

In this paper we have presented a variety of estimates of the impacts that properties listed for rent on Airbnb appear to have on the market value of residential properties in New York City. The direction and magnitude of these impacts has prompted widespread concern and considerable debate about the impact on urban structure and housing affordability in New York City and in other cities around the world. Many jurisdictions have responded by attempting to regulate or impose restrictions on the ability of Airbnb to operate or of property owners to makes use of Airbnb services.

We present intuitive and formal theoretical arguments that generally support, but do not ensure that this impact would be for house prices to increase in response to Airbnb listings as long as the Airbnb properties themselves are not the source of extensive or concentrated negative externalities. This impact is not guaranteed, however, and empirical investigation is required to determine the sign and magnitude of impact.

Our theoretical arguments suggest two possibilities: an increase in property values throughout the city that is greater in the center than at the periphery (if Airbnb properties facilitate an increase in population accommodated in the city), an increase in property values that is greater at the urban periphery and diminishes (or is negative) at the urban center (if Airbnb brings increased income to residents or increases the demand for space for each household). The first possibility is associated with a decline in equilibrium utility levels of residents. The second with an increase in utility.

We have presented several estimates of the likely range of impacts. A quick 'back-of-the-envelope' calculation based on income capitalization suggests that property values should increase about 17%. Hedonic analysis of house prices indicates that a doubling of the total number of Airbnb properties within 300 meters of a house is associated with an increase in property value of 6% to 9% (depending on model specification).

Consideration of the introduction of Airbnb as an experimental treatment to the housing market, and estimation of average treatment effects provides the most satisfactory approach to evaluation of the impacts of Airbnb on house prices. Our analysis indicates that subjecting a property to the treatment of having Airbnb properties available nearby when it is sold increases prices by 3.5% (for properties that are far from the center and whose 'treatment' consists of only a few Airbnb properties) to more than 65% for properties that are near the center and/or are 'treated' by having a larger number of local Airbnb properties.

Somewhat more speculatively, we note that our analysis is consistent with thinking of Airbnb as increasing local urban population (by attracting tourists), since this would generate a pattern of property value changes similar to those we estimate as having taken place. This increase in population, as desirable as it might be for certain individuals and the temporary occupants of the properties, is associated overall with a decline in equilibrium utility in the urban area. This observation helps to explain the concern of policy makers and the (occasional) vehemence of local opposition to Airbnb properties.

Despite the speculative assessment of utility impacts, and the clear evidence for impact on house prices, we advise caution in crafting policies that ban Airbnb or similar short-term private rentals altogether. Public policies that reduce house prices in pursuit of housing affordability by diminishing the efficiency with which an owner can make use of his or her property may fail to be welfare-improving, in the same way as a city that creates "affordable" housing by encouraging more crime hardly seems desirable. Evaluating the welfare consequences of Airbnb, and hence the appropriateness of any regulatory action to limit use of Airbnb services, requires deeper analysis than we have provided here and much deeper analysis than appears to have been undertaken to date.

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