ATTACHMENT 3

STUDIES/ARTICLES RESEARCHED BY COUNCIL AND STAFF

RESEARCH ARTICLE

Airbnb and neighborhood crime: The incursion of tourists or the erosion of local social dynamics?

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Abstract

The proliferation of internet-based home-sharing platforms like Airbnb has raised heated debates, with many in the general public believing that the presence of Airbnb listings can lead to an increase in crime and disorder in residential neighborhoods. Despite the importance of this debate to residents, policymakers, and other stakeholders, few studies have examined the causal linkage between Airbnb listings and crime in neighborhoods. We conduct the first such empirical test in Boston neighborhoods, focusing on two potential mechanisms: (1) the inflow of tourists might generate or attract crime; and (2) the creation of transient properties undermines local social dynamics. Corresponding to these mechanisms, we examine whether the number of tourists (approximated with reviews) or the prevalence of listings predict more incidents of private conflict, social disorder, and violence both concurrently and in the following year. We find evidence that increases in Airbnb listings–but not reviews–led to more violence in neighborhoods in later years. This result supports the notion that the prevalence of Airbnb listings erodes the natural ability of a neighborhood to prevent crime, but does not support the interpretation that elevated numbers of tourists bring crime with them.

Introduction

The expansion of internet-based short-term rental platforms like Airbnb has raised heated debates in recent years. Airbnb enables travelers and visitors to stay in idle private residential properties as an alternative to hotels. Consequently, it creates an inflow of tourists into residential neighborhoods without hotels where they were previously unlikely to go, potentially causing undesirable impacts (aka negative externalities) for these neighborhoods [1]. One of the concerns held by some in the general public and presented in multiple media reports is that the presence of Airbnb listings can lead to an increase in crime and disorder in a neighborhood. For example, an article in 2016 in the New York Times reported that residents in New Orleans were distraught at Airbnb guests' disruptive behaviors [2]. The story resulted in a city-wide request for stricter regulations on home-sharing activities. Another article from Splinter News told a broader story of how sharing economy platforms like Uber and Airbnb are exploited by criminals [3]. Similar concerns have even given rise to websites like AirbnbHell.com, which documents the dangers of using Airbnb services. However, despite a number of media claims and anecdotal evidence, few studies have examined the causal linkage between Airbnb listings (or short-term rentals more generally) and crime in neighborhoods, and those that have have done so largely descriptively [4]. Thus, there remains a need for a robust empirical test of this relationship that can inform residents, policy makers, and other stakeholders.

Short-term rentals and crime: Two potential mechanisms

Most of the discussions about short-term rentals and crime in neighborhoods rest on the logic that tourists might bring such issues, a relationship that has been investigated more generally by researchers in both criminology and tourism. Often, this relationship is framed in terms of routine activities theory [5], in which a crime is understood as requiring three minimal elements: a motivated offender, a suitable target, and the lack of a guardian. There are three hypotheses that arise from this framing. Ryan (1993) makes the case for two of these. One is that tourists make for suitable targets, either because they are known to have money on them or are more vulnerable when navigating an unfamiliar city. Second, he argues that because tourist locations are known to have many suitable targets, they attract more potential offenders, putting both tourists and residents at greater risk [6]. There is more evidence for the first of these two hypotheses, as at least three studies have found that tourists are more likely to be victimized than locals [7–13]. Third, some have noted that tourists might engage in criminal or disruptive behavior themselves. For example, Boivin and Felson (2018) found that urban neighborhoods with more visitors feature elevated rates of crime committed by visitors but no increase in crimes committed by locals [14]. Similarly, arguments against short-term rentals often hinge on the assumption that tourists might bring drunkenness or other unruly behavior with them. Such behaviors are more frequent in downtown areas and business districts with many shops, restaurants, and bars, but would be less familiar in a residential neighborhood that now has many short-term rentals [15].

We also note a second mechanism by which short-term rentals might impact neighborhood crime, one that is less prevalent in public discussions. It draws off of the sociological\criminological concept of social organization–that is, neighborhoods whose residents know and trust each other and share common values are more able to establish and enforce social norms [16]. In turn, they tend to have lower levels of crime [17]. One of the main factors that inhibits a strong social organization is residential instability, because it is hard to develop relationships and establish norms if a sizable proportion of the population is transient [18]. It would stand to reason, then, that if a sufficient number of units throughout a community have been converted to short-term rentals–the most transient form of occupancy possible–it can undermine the social organization and its ability to discourage and prevent crime. A strong social organization is also associated with and able to support various dynamics and processes subsumed under the term 'social capital,' including trust, reciprocity, and social cooperation [19]. Further, researchers focusing more on this latter set of terminologies has repeatedly found that numerous manifestations of social capital are associated with lower incidence of crime [20, 21]. Moreover, previous theoretical work have demonstrated an strong impact of community structure (measured by network modularity) on population level attributes such as cooperation, fairness and stability [22–26].

We then have two potential mechanisms by which short-term rentals can lead to increased crime in a neighborhood–by bringing tourists who then perpetrate crime and disorder, or by creating transience that undermines local social dynamics that might in turn mitigate or prevent crime. It is important to note that these mechanisms are not mutually exclusive and could be operating simultaneously. That said, we note two analytic considerations that might disentangle their presence. The first consideration is temporal. If issues generated by the prevalence of short-term rentals arise from the presence of tourists themselves, we would anticipate increases in Airbnb listings and crime to be nearly if not perfectly concurrent. In contrast, if an abundance of listings is undermining the social organization of the community and its natural ability to prevent and discourage crime, then there would be a more gradual erosion. In this case we would expect to see any effect of Airbnb listings on crime be lagged, increasing over time. The second consideration regards the way we measure the presence of Airbnb in a community. If tourists themselves are perpetrating crime and disorder, the focus should be on the quantity of tourists listings are bringing to the neighborhood, rather than the listings themselves. Alternatively, if the concern is transience, we will want to focus on the quantity of listings. We describe our measurement strategy for each in the next subsection.

Previous evidence and the current study

Whether those staying in Airbnb listings attract or perpetrate crime, or, alternatively, a large number of Airbnb listings undermine the social organization of the community, it has become a common perception that the rise of short-term rentals in a residential neighborhood will be accompanied by a rise in crime. This notion has only been examined by two empirical studies, though neither directly tests this causal claim. One study looking at the association only examined the correlation between crime and Airbnb listings and did not control for other neighborhood characteristics nor the temporal relationship between the arrival of Airbnb listings and shifts in the crime rate [4]. Another paper used policy implementations as a natural experiment, but analyzed only at the citywide scale [27].

Here we fill this gap in the literature by testing whether the presence of Airbnb leads to increases in crime across the neighborhoods of Boston, MA. As noted above, we use two measurement strategies to study the link between short-term rentals and crime. First, we quantify the influx of Airbnb-related tourists by tabulating reviews for Airbnb listings in the neighborhood. The measure of *usage* is drawn from [29]. Our second strategy focuses on the listings in a neighborhood, for which we employ two such measures. The more common measure in the literature is what we refer to as *density*, which is the number of listings divided by the total number of households. This measure is one step forward to what we expect to impact neighborhood social organization. However, it does not take into account the geographic distribution of these listings. To illustrate, consider two neighborhoods with the same number of households and the same number of Airbnb listings. In one, the listings are distributed throughout the neighborhood, in the other, they are concentrated in two condo buildings that have been effectively converted into unofficial hotels. It would seem likely that the former would have a more pernicious impact on the neighborhood's social networks by undermining relationships more broadly, whereas the impacts of the latter would be more contained at a handful of properties. Thus, we also create measure we refer to as *penetration*, which is defined as the proportion of buildings in the neighborhood with Airbnb listings. This better captures how Airbnb listings are distributed through the community, potentially better capturing how likely they are to impact the social organization. As described above, an association between usage and crime would be evidence that tourists are generating or attracting crime and disorder themselves. Meanwhile, if penetration or density are predictive of crime and disorder and usage is not, there is a stronger case that an abundance of listings in a neighborhood are undermining the social organization.

We examine the relationships between the measures of Airbnb usage, penetration, and density and three types of social disorder and crime: public social disorder (e.g., drunkenness, loitering), private conflict (e.g., landlord-tenant disputes, vandalism), and violence (e.g., fights), all per 1,000 persons in a neighborhood. This allows us to examine in a nuanced way the nature of the impact that short-term rentals might have on neighborhoods. We use fixed effects models to conduct these analyses, comparing the relationships between these variables from 2011–2017, as Airbnb went from a minor to more major factor in Boston neighborhoods. As noted above, the two mechanisms by which short-term rentals might impact neighborhoods–either the tourists generating or attracting crime themselves, or the prevalence of listings eroding the social organization–would operate on different time scales. If the presence of tourists is responsible for crime, we would anticipate the impacts to occur in the same year as the increase of usage. The erosion of the social organization would take more time to result in elevated crime, lagging increases in listings by one or more years. Thus, we run the difference-in-difference fixed effects models with the Airbnb measures as measured concurrently with the crime outcome measures, with a one-year lag between the Airbnb measures and crime and disorder, and then with a two-year lag. Importantly, this work adds a rigorous empirical perspective to the ongoing debate regarding the negative externalities of short-term rental platforms such as Airbnb.

Data and methods

Measuring Airbnb presence

We use the period between 2011 to 2018 to quantify the presence of Airbnb in Boston. To estimate the presence of Airbnb in a neighborhood, we obtained datasets from InsideAirbnb.com, an independent, non-commercial website that scrapes and publishes longitudinal Airbnb listings' records for cities across the world for the purpose of research. InsideAribnb.com has published these data annually since 2015, but Airbnb entered Boston in 2009. In order to overcome this limitation, we leveraged the "host since" field, which indicates the date a property became an Airbnb listing, to estimate which Airbnb listings were present in each year 2011–2014. Koster et al. (2018) took a similar approach using the date of a listing's first review, but we found that the "host since" variable more consistently had a value and would be more precise in any case. InsideAirbnb.com also publishes a separate dataset on the reviews received by each listing along with the listings data [28]. The reviews datasets have been used to estimate the amount of tourists brought by Airbnb services [29, 30]. We note that although we consider the start year of our study as 2011, there were still some Airbnb units in Boston as early as 2008 that are not considered in this study. This should not impact the results given the limited nature of this presence; however it might have implications for testing pre-treatment parallel trends in the DID analysis as we will explain in the *Robustness Check* Section.

Following the practice of Horn & Merante (2017), we use census tracts to approximate neighborhoods (avg. population = 4,000; 168 with meaningful population in Boston). We then linked listings to the containing census tract, allowing us to calculate neighborhood-level measures of Airbnb's prevalence. Though listings are not necessarily geographically precise, InsideAirbnb.com indicates that listings are 0–450 feet from the actual address. Meanwhile, census tracts cover .5 mile radius, meaning that most listings should fall in the appropriate census tract.

We use three measures to quantify the level of Airbnb presence in each tract. Specifically, these aim to operationalize the quantity of listings and the quantity of tourists they bring to the neighborhood. For listings, our primary measure *penetration* sought to capture how they were spatially distributed across the neighborhoods. It was calculated as the number of unique addresses with listings divided by the number of parcels (lots that contain one or more units, per the City of Boston's Assessing Department) in the census tract, thereby approximating the number of buildings with at least one Airbnb listing. This might be a more appropriate proxy, for instance, when Airbnb listings are many in a neighborhood but concentrated in one or two condo buildings, thus geographically constraining their overall impact. For robustness, we also measured *density*, or the ratio of Airbnb listings to housing units. This measurement has been widely adopted in previous studies on Airbnb [31, 32]. The quantity of tourists attracted was operationalized as *usage*, calculated as the number of reviews divided by housing units in a census tract as recommended by Schild (2019) [29].

Using 911 call data to measure crime activity

We utilized three variables measuring crime and disorder developed by the Boston Area Research Initiative from 911 dispatches from 2011–2018. These measures were calculated as the rate per 1,000 residents of events falling into a pre-determined set of categories from the dispatches. They include: public social disorder, including intoxicated individuals, lewdness, and drunken disturbances; private conflict includes issues like landlord/tenant trouble, breaking and entering, and vandalism; and violence includes events like armed robberies, assaults, a person with knife, and fights.

Estimation strategies

The key research question we ask in this study is whether the proliferation of Airbnb in a neighborhood lead to higher level of crime events in that neighborhood. The panel dataset we assembled at the census tract-level allows us to employ a generalized multiple time period, multiple group Difference-in-Difference (DID) design, in which Airbnb presence acts as a continuous "treatment", predicting changes in crime in a neighborhood.

The estimated equation is:

$$Y_{i,t} = \alpha + \gamma Airbnb_{i,t-\tau} + \delta X_{i,t} + \eta_i + \beta_t + \varepsilon_{i,t} \qquad (1)$$

where i represents the census tract, t represents the year, and τ is used to introduce time lag and lead for the treatment variable. $Y_{i,t}$ is the crime level measured by the number of private conflict, social disorder, and violence events per 1,000 people, $X_{i,t}$ is a vector of time-variant neighborhood-level controls, and γ is the estimated causal effect of Airbnb presence. η and β are the neighborhood (tract) and year fixed effects, respectively, capturing both time-invariant characteristics of tracts and spatially-invariant characteristics of years (for example, a city-wide increase in Airbnb prevalence or crime level). We report the results based on using *income* as the main tract-level control variable, although we test a number of other controls for robustness test. $Income_{i,t}$ measures the median household income (drawn from the American Community Survey's five year estimations at the census tract-level, appropriate to the year in question. We estimate Eq (1) using deviation from mean approach, and standard errors are clustered at the tract level.

To further test the direction of causality for the results, we use a lag/lead analysis in the spirit of Granger [33, 34]. This method is used when the sample includes multiple years and uses both lead and lagged versions of the treatment variable (τ can be both positive and negative).

Results

Descriptive analyses

Before testing our main question, it is useful to examine the growth and distribution of Airbnb activities in Boston. As depicted in Fig 1, Airbnb had limited presence in Boston at first, with a negligible number of listings and reviews before 2014. There was rapid growth, however, between 2014 and 2018, over which time the number of listings more than doubled from 2,558 to 6,014. There were also nearly 80,000 total reviews by 2018. That is not to say, however, that this growth was uniform across neighborhoods. Certain census tracts were the first to have a measurable presence of Airbnb and then proceeded to have high levels of Airbnb listings. Fig 2 shows how Airbnb services increased from 2010 to 2018 and across census tracts in Boston. We focus on two main measures to capture Airbnb activities: penetration, or the proportion of buildings with at least one listing; and usage, or the number of reviews per housing unit in the neighborhood. As indicated in Fig 2a, by 2018, the tracts with the highest penetration of Airbnb had listings in as many as 40% of buildings. Likewise, the neighborhoods with the highest level of usage had as many as one review per housing unit. In contrast, in many other tracts the presence of Airbnb was limited or even absent throughout the study period. Meanwhile a handful of tracts started with very low Airbnb presence and then witnessed rapid growth of Airbnb-related activities.

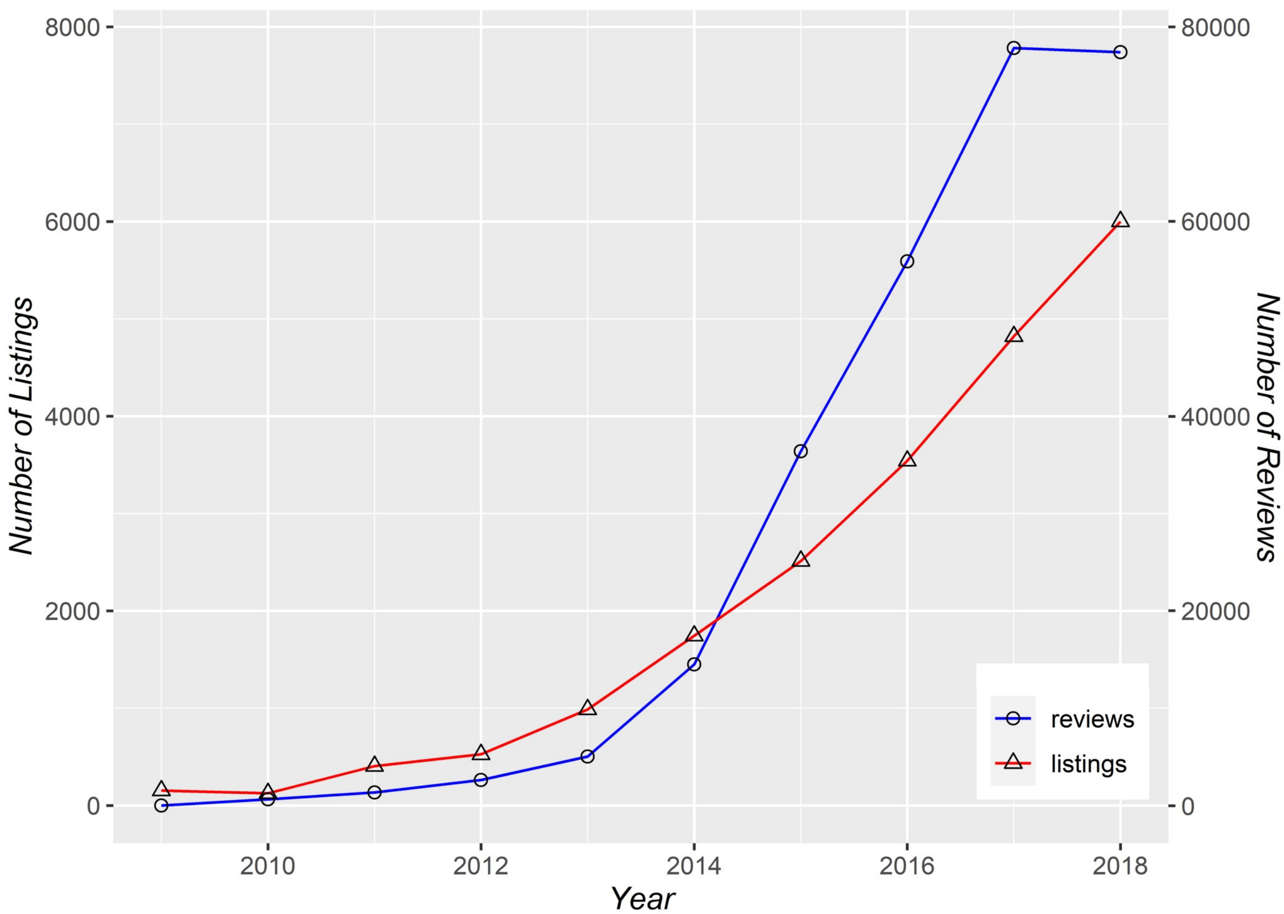

Fig 1. Airbnb's expansion in Boston. The number of Airbnb listings and reviews in Boston between 2009 and 2018.

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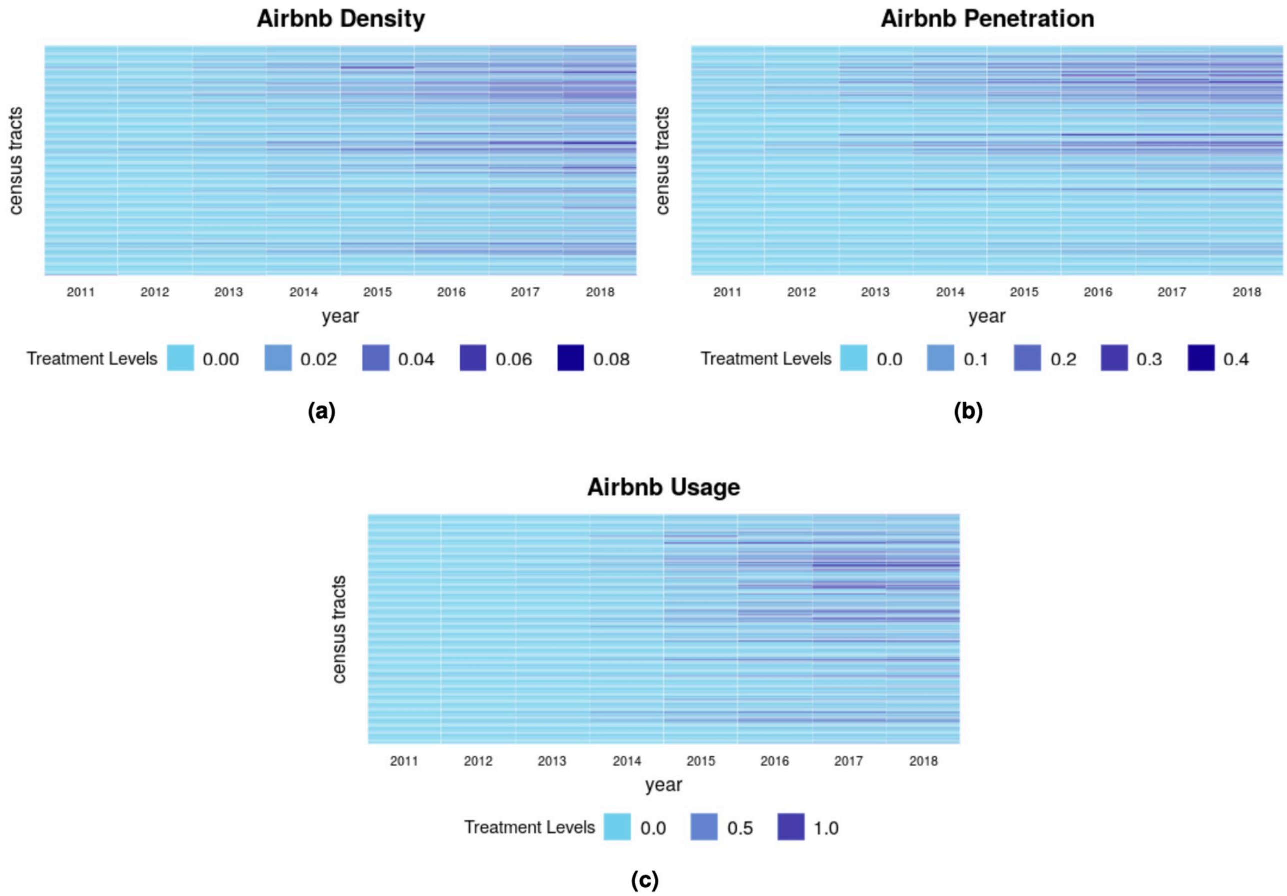

Fig 2. Airbnb's presence in Boston. (a) Airbnb density, (b) Airbnb penetration, and (c) Airbnb usage. Each row represents a census tract from 2011 to 2018. The darker the color, the higher the Airbnb presence. Tracts are in the same position in each panel, meaning we can compare panels to confirm that most tracts with high level of presence on one measure scored similarly on the other measures.

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Fig 3 maps the spatial distributions of the three measures of Airbnb supply over time. For Airbnb density (Fig 3a), we see that census tracts in the urban center (northeast on the map) show relatively high Airbnb presence from the beginning, but that in recent years the tracts with the highest level of Airbnb penetration emanate further out into surrounding, more residential neighborhoods.

The concurrent and lagged impacts of Airbnb on crime

We use difference-in-difference models (Eq (1)) to test whether a rise in the prevalence of Airbnb in a census tract in one year predicts increases in crime and disorder in the following year. We focus on two ways in which short-term rentals can impact a neighborhood. The first is through two measures of the quantity of listings in a neighborhood: the penetration of Airbnb, measured as the proportion of buildings with at least one listing; and the density of Airbnb, or the ratio of listings to total households. We believe the latter is the stronger measure for our purposes (see Introduction for more), but include both as a check. The second strategy is to capture the amount of tourists brought in by listings via the measurement of usage, or the ratio of user reviews to households. The model outcomes include three measures of crime and disorder: private conflict between people who live together, like landlord-tenant disputes; public social disorder, like drunkenness and noise complaints; and public violence, including

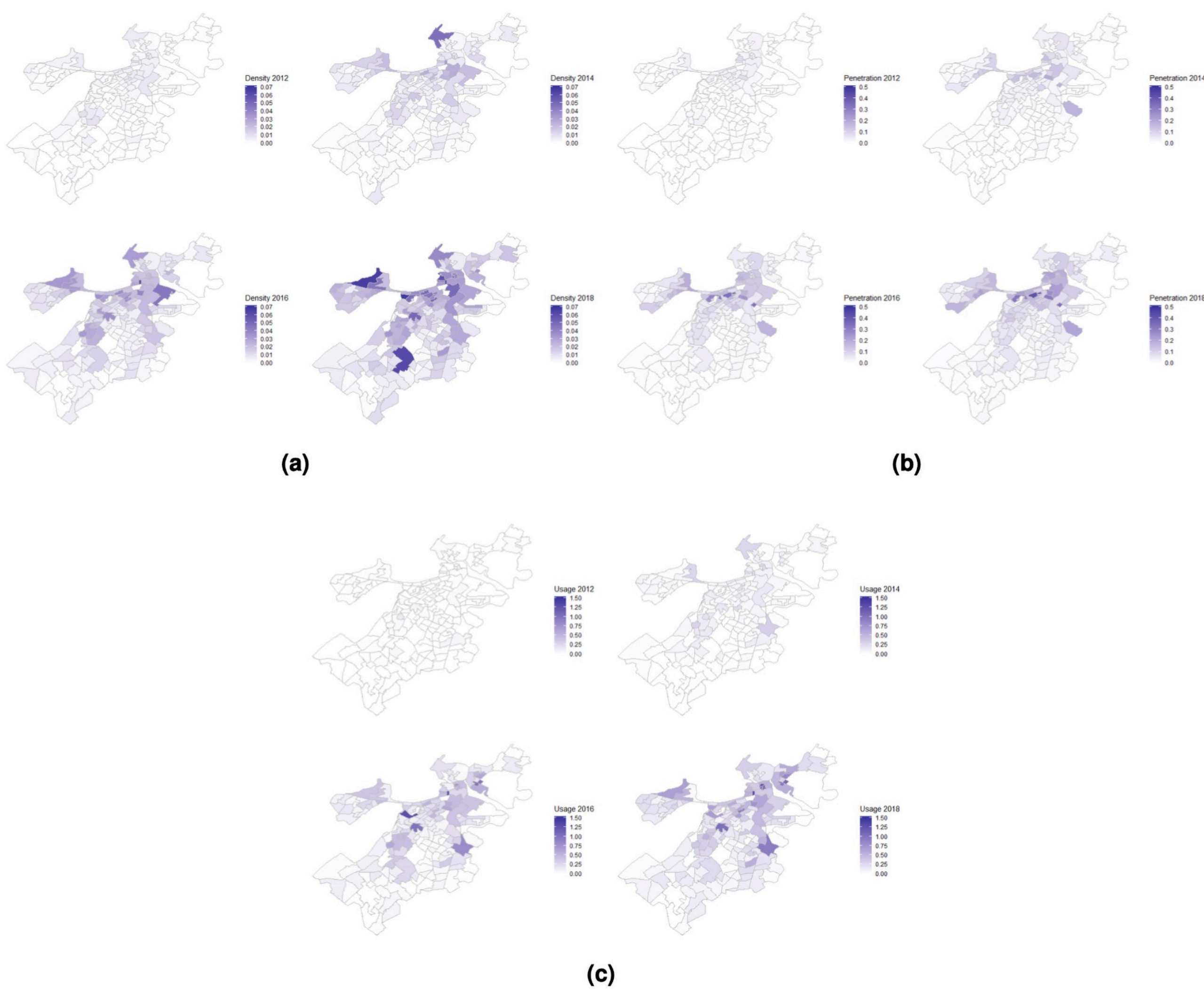

Fig 3. Evolution of spatial distributions of Airbnb in Boston. (a) Airbnb density, (b) Airbnb penetration, and (c) Airbnb usage in 2012, 2014, 2016, and 2018.

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fights (see Methods). The models control for tract-level and year fixed effects. In order to make the parameter estimates that follow more interpretable, we note that the average census tract in the average year experienced 11.32 events of private conflict, 7.68 events of public social disorder, and 28.58 events of public violence per 1,000 residents.

We begin by testing the relationship between Airbnb prevalence and crime in the same year (See Table 1). We see only one significant effect, which is Airbnb penetration predicting higher levels of violent crime ($\beta = 0.328$, $p < 0.05$). Otherwise, density and usage were not associated with any forms of crime, nor were social disorder or private conflict associated with any of the Airbnb measures.

We then compare these results to models that test the relationship between Airbnb measures from the previous year on crime (i.e., one-year lags). In these models, neighborhoods with a higher level of Airbnb penetration saw rises in violent crime in the following year ($\beta = 0.546$, $p < 0.0001$), and notably to a greater extent than the concurrent measure of penetration. There was still no corresponding effect on public social disorder or private conflict,

Table 1. Same-year DID regressions on social disorder and crime.

	Events of Private Conflict	Events of Social Disorder	Events of Violence
Airbnb Density (%)	-0.207	0.080	1.226
	(0.207)	(0.285)	(0.621)
Airbnb Penetration (%)	0.005	-0.004	0.328*
	(0.035)	(0.073)	(0.133)
Airbnb Usage (%)	0.000	-0.004	0.025
	(0.008)	(0.011)	(0.021)
Tract FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	1171	1171	1171
F (Density)	0.88	1.20	2.17
F (Penetration)	0.36	0.97	3.13
F (Usage)	0.36	0.93	0.77

Note: clustered standard errors are displayed in parenthesis. Control variable is median household income. The average census tract in the average year experienced 11.32 events of private conflict, 7.68 events of public social disorder, and 28.58 events of public violence per 1,000 residents.Significance levels:

* p<0.05;

** p<0.01;

*** p<0.001.

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however. Airbnb density in the previous year was also associated with higher levels of violent crime, albeit at a lower significance, and thus magnitude, relative to penetration ((β = 1.407, $p < 0.05$). Airbnb usage had no effect on any of the three measures in the following year(Table 2).

Table 2. One-year lagged independent variables.

	Events of Private Conflict			Events of Social Disorder			Events of Violence		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Airbnb Penetration (lag 1)	0.041			-0.115			0.546***		
	(0.039)			(0.118)			(0.133)		
Airbnb Density (lag 1)		-0.112			-0.426			1.407*	
		(0.227)			(0.293)			(0.614)	
Airbnb Usage (lag 1)			0.001			-0.011			0.037
			(0.009)			(0.016)			(0.021)
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1004	1004	1004	1004	1004	1004	1004	1004	1004
F	0.62	0.16	0.04	0.8	1.32	0.79	8.7	2.69	1.56

Note: clustered standard errors are displayed in parenthesis. Control variable is median household income. The average census tract in the average year experienced 11.32 events of private conflict, 7.68 events of public social disorder, and 28.58 events of public violence per 1,000 residents.

Significance levels:

* p<0.05;

** p<0.01;

*** p<0.001.

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Table 3. Two-year lagged independent variables.

	Events of Private Conflict			Events of Social Disorder			Events of Violence		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Airbnb Penetration (lag 2)	0.097*			-0.162			0.553***		
	(0.041)			(0.107)			(0.119)		
Airbnb Density (lag 2)		0.039			-0.884			1.167*	
		(0.215)			(0.472)			(0.529))	
Airbnb Usage (lag 2)			0.014			-0.036			0.037
			(0.013)			(0.029)			(0.027)
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	837	837	837	837	837	837	837	837	837
F	3.41	0.53	1.02	2.71	3.71	2.79	10.8	2.43	1.04

Note: clustered standard errors are displayed in parenthesis. Control variable is median household income. The average census tract in the average year experienced 11.32 events of private conflict, 7.68 events of public social disorder, and 28.58 events of public violence per 1,000 residents.

Significance levels:

* $p<0.05$;

** $p<0.01$;

*** $p<0.001$.

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If the increase in crime rate is driven by changes in social organization, we expect to see the effect to persists and possibly strengthen over a more extended period of time. To further test the validity of this mechanism,we repeated the previous analysis, this time with a two-year lag on independent variables.

Results of the two-year lagged analysis are in general agreement with those with one-year lag in terms of the impact of Airbnb penetration on events of violence. Moreover, Airbnb penetration not only predicted increased violence at this time scale, but also showed a moderate impact on events of private conflict ($\beta = 0.097$, $p < 0.05$), an effect that was not present in the one-year lagged analysis. The effects of Airbnb usage and density also concurred with the one-year lagged analysis (Table 3).

Robustness checks

The intent here has been to test whether Airbnb activity in a neighborhood impacts crime, but there is an alternative reverse effect interpretation to our results that need to be considered: That crime leads to Airbnb listings, possibly by deterring property owners from renting long-term or living there themselves–could be true. Rejecting the reverse causality in the DID models is often carried out by testing the pre-treatment parallel trends. However, directly applying the standard tests for parallel trends, such as event-study analysis, is not possible here, because on the one hand, the treatment variable (Airbnb Presence) is both continuous and staggered which makes event-study analysis less reliable and difficult to interpret. On the other hand, our data starts from 2011 where Airbnb had already been present in many neighborhoods (See the Section on *Measuring Airbnb Presence*), preventing us from reliably transforming the treatment into a binary variable that could be used in subsequent event-study analysis (similar to [35]). Because of these reasons and to confirm the direction of causality, we took two additional steps. In the first step, we reran our models with the Airbnb measures from one and two

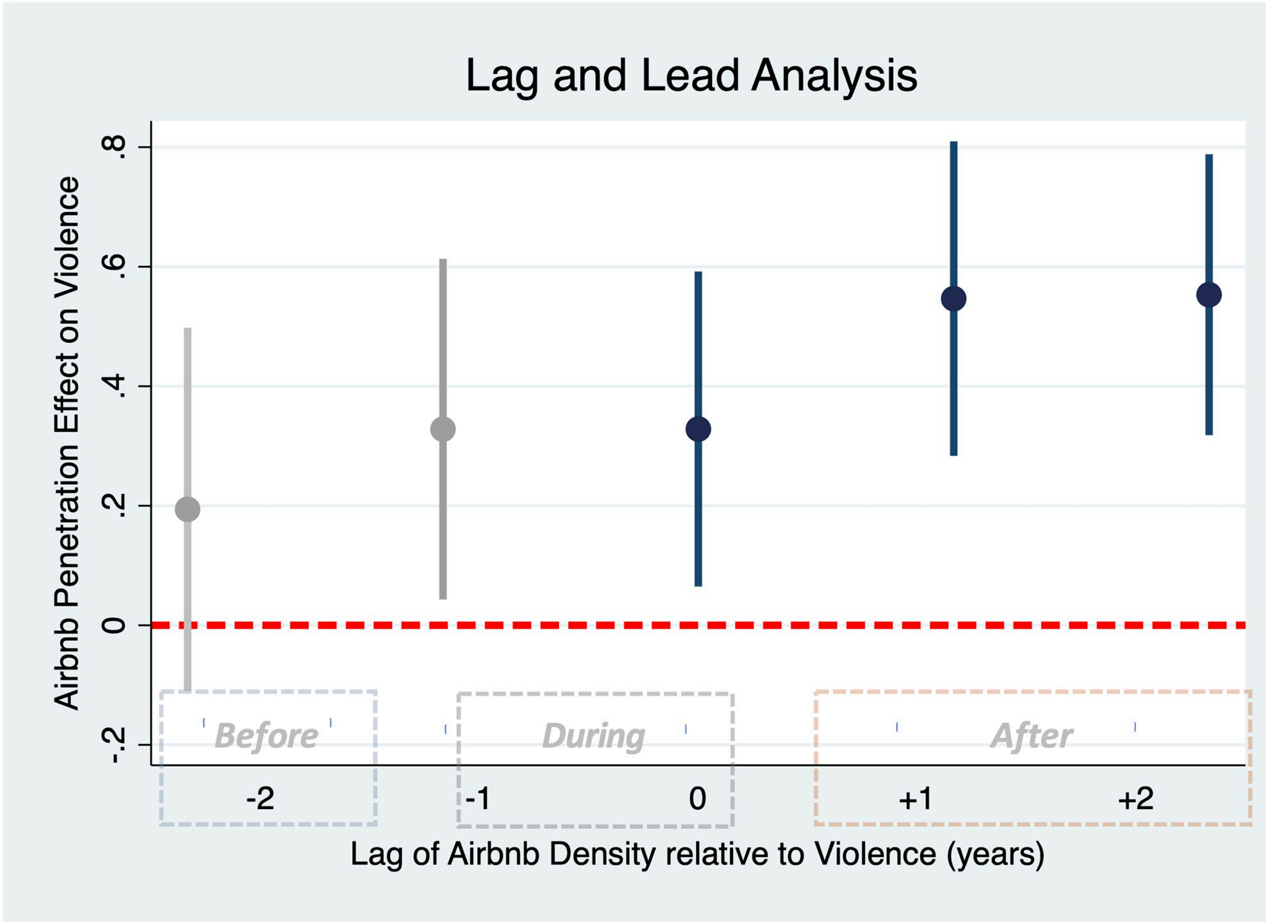

Fig 4. Result of the lag and lead analysis. The figure shows the DID regression coefficients and the corresponding standard errors for the effect of Airbnb density on violence, before, during, and after the effect. Results confirm the direction of causality from Airbnb penetration on violent crimes and show that Airbnb penetration has a significant positive effect on violence, especially with a time delay, but the opposite is not true, as evident from the non-significant effect of a 2-year lead in Airbnb penetration on criminal activities. Complete results are presented in the SI document.

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years after the year of the crime measures (See the Methods section.). This method follows the logic of Granger Causality and was popularized by [36] in assessing the impact of unjust dismissal doctrine on outsourcing. Moreover, a recent work by Schmidheiny and Siegloch [37] shows that the event-study analysis and a version of the lag/lead model are equivalent for the case of DID with discrete treatments.

Fig 4 shows a graphical representation of the DID regression coefficients and associated error bars for violent crimes for different time lags(-2 years to +2 years) of Airbnb penetration measure(Full results reported in the SI). The coefficient for two years prior to the treatment (the two-year lead) saw no significant effect on crime, suggesting that with sufficient lead time, these results are consistent with an interpretation of Airbnb's presence impacting crime and not the reverse.

The one-year lead model still showed an effect of Airbnb penetration on violence, though attenuated relative. This is not entirely surprising since first of all, the treatment variable is continuous, which—unlike [36]—makes it challenging to clearly separate the treatment year from the immediate prior year (the year with one year lead). Moreover, that crime data are aggregated at a yearly basis and our model cannot differentiate between criminal activities at the beginning and end of the year. These reason suggests that due to the resolution and continuous nature of the data, the one year lead is colinear with the zero lead year and can be interpreted, in part, as a period *during* treatment, as marked in the figure. Thus, we need to consider the coefficient for two years prior to the treatment to be able to reject the possibility of reverse causality.

A second and related concern could be the potential bias due to omitted variables. Though the DID models control for the initial conditions of neighborhoods, they do not necessarily control for trends in these variables that parallel the increases in both Airbnb presence and crime. For example, there is some evidence that gentrifying neighborhoods experience increases in certain types of crime [38], and Airbnb listings have also been associated with gentrification [39]. To address this concern and as the second robustness check steps, we reran the models incorporating shifts in four demographic factors–percentage Black residents, percentage Hispanic residents, median income, and homeownership rate–that are often correlated with crime (and are in our data) or believed to be correlated with short-term rentals (e.g., resident-owners are less likely to put their homes up for short-term rental on a regular basis as they live there). We did this by assigning indicators from American Community Survey's five-year estimates for 2009–2013 to data for 2011–2013, and estimates for 2014–2018 to data for 2014–2017. This is consistent with guidance to not include overlapping estimates in a single analysis [40]. These models did not impact any of the significant effects from the original set of models, indicating our findings were robust to shifts in demographics.

Discussion and conclusion

This study tested the hypothesis that the arrival and growth of Airbnb, or home-sharing platforms in general, may increase crime and disorder in neighborhoods, focusing specifically on private conflict, public social disorder, and violence. We find that the answer is rather nuanced. Airbnb prevalence in a neighborhood appears to be associated with increases in violence, but not with public social disorder or private conflict. Interestingly, the effect on violence was only consistent visible for the measure of Airbnb penetration–or the extent to which buildings in the neighborhood have one or more listings (and for the measure of density, or the listings per household in the two-year lags). It was never present for overall usage, or the estimated quantity of Airbnb guests. Further, the effect of penetration on violence appears to emerge and strengthen over multiple years.

The specific findings suggest that the impacts of short-term rentals on crime are not a consequence of attracting tourists themselves. Instead, the results point to the possibility that the large-scale conversion of housing units into short-term rentals undermines a neighborhood's social organization, and in turn its natural ability of a neighborhood to counteract and discourage crime, specifically violent crime. Further, the lagged effects suggest a long-term erosion of the social organization, which would stand in contrast to the more immediate impacts that the presence of tourists would be expected to have. We of course have not directly tested whether social organization is indeed the intervening variable, but it seems clear that the issue is not the tourists themselves but something about how the extreme transience of a short-term rental unit fails to contribute to critical neighborhood social dynamics. We do note that the effects were exclusively on public violence, apart from penetration predicting higher private conflict in the two-year lag. This observation might be for a few reasons. First, social organization is often argued to be particularly important for managing behaviors in public spaces relative to private ones [18]. In addition, public social disorder as measured here, which includes public drunkenness, panhandling, and loitering, is heavily concentrated in Boston's commercial districts. Thus, such events may be unlikely in residential neighborhoods even with the erosion of social organization. The lack of effects on social disorder, especially drunkenness, might also be taken as additional evidence that tourists staying in short-term rentals are not systematically bringing nuisances to the neighborhood.

The results have important practical implications. To our knowledge, this paper is the first study to robustly test this particular externality of Airbnb at the neighborhood level. Airbnb-related crimes are viewed as a possible consequence of the home-sharing platform because the costs of these incidents are not addressed by the transactions between Airbnb hosts and guests. Instead, these costs are shouldered by increased expenditures for law enforcement and disturbances to neighbors. It is striking to see that the issue is not the visitors themselves but the conversion of units into short-term rentals. In a certain light, this observation is analogous to the effect of Airbnb on housing prices [31, 41–43]. In the one case, Airbnb has removed material capital from the market, raising prices for renters; in the other, Airbnb removes social capital from the neighborhood in the form of stable households, weakening the associated community dynamics.

The apparent unimportance of the tourists themselves might come as something of a surprise given the conceptual and empirical support for the impacts of tourism on crime. It suggests multiple potential explanations. First, although Airbnb has seen notable growth, it might not bring a sufficient quantity of tourists to a neighborhood to have a sustained impact. If there are only a handful of tourists in a neighborhood, the opportunity might not be rich enough to attract predatory crime. Given that we do not expect that other cities have markedly higher Airbnb presence than Boston, we believe this interpretation is extensible to other locales. Second, Airbnb travelers may behave differently in "true" tourist areas than when in the residential neighborhood they are staying in, which in turn could mean that they are less likely to be disorderly or to call attention to themselves as suitable targets.

We note two limitations to our research that call for future studies. First, we have tested this hypothesis in a single city, owing to the availability of both Airbnb listings and 911 dispatches for Boston. Future studies should replicate this analysis in other cities, especially those of different sizes or demographic makeup. Second, we examined a single, hypothesized negative externality of short-term rentals. It does not on its own tell the whole story. Airbnb might have other impacts on neighborhoods–both good and bad. These other relationships require further empirical investigation. Currently, a number of papers have explored how urban planners and policy-makers could respond to potential externalities imposed by Airbnb on urban neighborhoods [44–46], and such efforts will be better informed as we better understand the multifaceted impacts Airbnb can have.

Supporting information

S1 File.
(PDF)

S1 Data. Airbnb and crime data.
(CSV)

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Market Shifts in the Sharing Economy: The Impact of Airbnb on Housing Rentals

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Abstract

This paper examines the impact of Airbnb on the local rental housing market. Airbnb provides landlords an alternative opportunity to rent to short-term tourists, potentially leading some landlords to switch from long-term rentals, thereby affecting rental housing supply and affordability. Despite recent government regulations to address this concern, it remains unclear how many and what types of properties are switching. Combining Airbnb and American Housing Survey data, we estimate a structural model of property owners' decisions and conduct counterfactual analyses to evaluate various regulations. We find that Airbnb mildly cannibalizes the long-term rental supply. Cities where Airbnb is more popular experience a larger rental supply reduction, but they do not necessarily have a larger percentage of switchers. Affordable units are the major sources of both the negative and positive impacts of Airbnb: they cause a larger rental supply reduction, which harms local renters; they also create a larger market expansion effect, which benefits local hosts who own affordable units and may be less economically advantaged. Policy makers need to strike a balance between local renters' affordable housing concerns and local hosts' income source needs. We also find that imposing a linear tax is more desirable than limiting the number of days a property can be listed. We propose a new convex tax that imposes a higher tax on expensive units and show that it can outperform existing policies in terms of reducing cannibalization and alleviating social inequality. Finally, Airbnb and rent control can exacerbate each other's negative impacts.

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1 Introduction

Sharing economy platforms have affected marketing mix decisions (e.g., product, pricing, and distribution channels) by providing an additional channel for individuals to market their products and services. For example, peer-to-peer marketplaces for short-term accommodations such as Airbnb, HomeAway, and VRBO have emerged as an alternative channel for landlords to market their properties to short-term tourists in addition to the traditional long-term rental market for local residents. These home-sharing platforms have grown at an exponential rate in recent years. Airbnb, the most popular platform, had over six million listings around the world as of March 2019—more listings than the hotel rooms from the six largest hotel groups combined.[1]

Given the opportunity to rent to short-term tourists, some property owners may switch from the traditional channel of long-term rental to the new channel of Airbnb because the yields can be higher with Airbnb than in the long-term rental market.[2] Such switching behavior could impact rental housing supply and affordability. Motivated by these concerns, city regulators launched various policies on short-term rentals, especially in cities where affordable housing has been an issue. For example, the City of Los Angeles approved new rules for Airbnb-type rentals in December 2018, following more than 3.5 years of debate since the law was first proposed.[3] Similarly, San Francisco saw a controversial debate and changes in the scope of the city's short-term rental regulation, which first went into effect in February 2015.[4] There are two prevailing types of regulations. The first type limits the number of days that a property can be listed on short-term rental platforms (e.g., a maximum of 90 days in San Francisco and 120 days in Los Angeles).[5] The second type charges a transient occupancy tax on the listing price (e.g., 8.5% in Philadelphia and 14% in Los Angeles), which is similar to a hotel occupancy tax.[6] By 2020, many cities had imposed similar regulations on Airbnb. However, most of these policies were launched without empirical evidence. It remains unclear how Airbnb has affected the rental housing market.

In this paper, we seek to answer two questions. First, how does Airbnb affect the supply and affordability of rental housing? In particular, we examine how many units are taken off the rental market (i.e., the impact

[1]See https://press.airbnb.com/airbnb-hosts-share-more-than-six-million-listings-around-the-world/

[2]See https://tranio.com/articles/airbnb_a_game-changer_for_the_commercial_property_market_4982/. In addition, see https://www.forbes.com/sites/garybarker/2020/02/21/the-airbnb-effect-on-housing-and-rent/?sh=3d580ee32226.

[3]See https://www.latimes.com/local/lanow/la-me-ln-airbnb-rental-ordinance-20181211-story.html.

[4]In a 2015 ballot measure in San Francisco, 55% of voters rejected Proposition F, which would have reduced the number of days that owners can rent out their properties from 90 to 75. See https://www.theguardian.com/us-news/2015/nov/04/san-francisco-voters-reject-proposition-f-restrict-airbnb-rentals. Later, in 2016, San Francisco approved a new rule that requires short-term rental websites such as Airbnb to display each host's registration number next to their listings or email the information to the city's short-term rentals office. This rule supplements San Francisco's existing short-term rental regulations that require hosts to register with the city's short-term rentals office. See http://fortune.com/2016/06/07/sf-airbnb-new-rules/.

[5]See https://www.airbnb.com/help/article/864/los-angeles-ca#nightlimits.

[6]See https://www.airbnb.com/help/article/2509/in-what-areas-is-occupancy-tax-collection-and-remittance-by-airbnb-available.

on rental supply) and the types of properties that are taken off the rental market (i.e., the impact on rental affordability). Second, what is the impact of various regulations on short-term rentals? Answering these questions requires an understanding of the underlying trade-offs, or benefits and costs, for property owners. The benefits of renting can be directly observed from the prices and occupancy rates in the long-term market and on Airbnb. However, the costs of renting and how they differ by demographics, properties, and cities are unknown.

We estimate a structural model of property owners' decisions using Airbnb listings data and American Housing Survey data. We recover the underlying heterogeneous hosting costs, which allow us to simulate market outcomes in the absence of Airbnb to examine its impact and evaluate market outcomes under different policies. In the model, property owners first make a discrete choice based on their availability type. Owners who are available for the full year choose among Airbnb, long-term rental, and an outside option of keeping the properties vacant. Owners who are available for part of the year choose between Airbnb and the outside option. This decision is usually made yearly, as the length of rental leases is typically one year. Second, if owners choose Airbnb, they decide the number of days to list their properties on Airbnb, which can be a monthly decision. The two decisions are linked in that the ex ante expected profit from the second decision affects the first decision. The hosting costs and host availability are allowed to be heterogeneous by property characteristics, host demographics, various metro area characteristics (e.g., population, density, mortgage affordability, wage and employment in the accommodation industry, how long Airbnb has been present, and how favorable city regulations are to short-term rentals) and over time.

The results show that Airbnb mildly cannibalizes the long-term rental supply but creates a market expansion effect. The level of cannibalization varies significantly across metro areas. Interestingly, we find that although the rental supply reduction is larger in metro areas where Airbnb is popular, the percentage of switchers is not necessarily larger in those areas. For example, Miami and New York are among the cities with the highest Airbnb popularity and the largest rental supply reduction. However, their percentages of switchers are among the lowest, suggesting that most of the Airbnb listings in Miami and New York are from market expansion rather than cannibalizing the rental supply. Policy makers must take a holistic view when evaluating Airbnb's impact.

Importantly, the results show that affordable units are the major sources of both the negative cannibalization impact and the positive market expansion impact of Airbnb. We find suggestive evidence that Airbnb does raise affordable housing concerns, as the rental supply reduction is the highest among affordable units. However, the market expansion effect is also the largest for affordable units, as the fraction of non-switchers is the largest for affordable units on Airbnb. Although Airbnb harms local renters by reducing affordable rental supply, it also serves as a valuable income source and benefits local hosts who own affordable units;

these hosts are likely to be less economically advantaged than hosts who own expensive units and benefit more from additional income sources. Therefore, policy makers need to trade off between local renters' affordable housing concerns and local hosts' income source needs.

In the counterfactual analysis, we evaluate two sets of policies related to the supply and affordability of rental housing. The first set of counterfactuals is motivated by recent regulations on short-term rentals. Policy makers are continuously searching for effective policies to prevent switching away from long-term rentals, especially in cities with tight housing markets such as San Francisco, New York, and Los Angeles. In addition to limiting the length of listings on Airbnb, local municipalities also require hosts to collect certain taxes from guests, similar to a hotel occupancy tax. We examine these two existing policies (day limit and a linear tax) and further propose a new convex tax that imposes a higher tax on expensive units and a lower tax on affordable units, which is motivated by our finding that the cannibalization rate or percentage of switchers is larger for expensive units.

A desirable policy should maintain the positive impact of Airbnb (non-switchers or market expansion) and reduce the negative impact of Airbnb (switchers or cannibalization). Therefore, we assess the desirability of the three policies along three dimensions: (1) the ability to reduce the cannibalization rate or percentage of switchers; (2) the ability to reduce the fraction of total host profits earned by owners of luxury units; and (3) the ability to reduce the fraction of total host profits earned by economically advantaged hosts (e.g., high-income, older, or high-education hosts). The second and third measures relate to social inequality because they capture potential differential policy impacts on heterogeneous hosts. In particular, Airbnb provides the hosts an additional income source; imposing regulations can induce a redistributive effect among Airbnb hosts and affect income equality. A desirable policy should prevent the distribution of income among hosts from being skewed to those economically advantaged hosts who own expensive units and already have abundant resources. We find that the proposed convex tax outperforms the other two policies along all three dimensions. The linear tax is the second-best policy, and the day limit is the worst.

The second set of counterfactuals focuses on rent control policy, which limits rent in the long-term rental market. Economists are virtually unanimous in concluding that rent controls are destructive because they reduce the available housing supply. When a rent control policy is imposed, property owners choose not to rent out their units for long-term rental. Despite the known adverse impacts, the states of California, Maryland, New Jersey, New York, Oregon, and the city of Washington D.C. still have some rent control or stabilization policies on the books (as of March 2019).[7] We show that the negative effect of rent control policies is aggravated when Airbnb is available because Airbnb serves as an additional profitable option for property owners and can further motivate them to switch away from the long-term rental market.

[7]See https://www.curbed.com/2019/3/8/18245307/rent-control-oregon-housing-crisis

The results have strong policy implications for short-term rentals and affordable housing. Airbnb has been debated and regulated in the cities it has entered. For policy makers, assessing the impact of Airbnb is difficult, as it requires knowing whether the properties would have been in the rental market had Airbnb not been available. Our model can be used to assess the impact of Airbnb on rental supply and affordability. The results provide a detailed profile of potential switching hosts and properties, which can serve as a foundation for policy making. We also provide a thorough evaluation of the desirability of various short-term rental regulations and propose a new policy that can outperform existing policies. Finally, we show that rent regulation must be implemented with extra caution when Airbnb is available, as lower profits from long-term rentals can cause landlords to switch to Airbnb.

2 Literature Review

This paper contributes to the literature by addressing important policy-driven questions regarding whether and how Airbnb has impacted the rental housing market. There have been continuous concerns that hosts on the long-term rental market may switch to Airbnb, causing a reduction in rental housing supply and threatening housing affordability. These concerns motivated many cities to impose various regulations on Airbnb, including charging a transient occupancy tax and limiting the number of days that a property can be listed. However, most of these policies were launched without empirical evidence. The existing literature on the potential switching behavior of the hosts is scant. The effectiveness of current short-term rental regulations also remains unclear.

Indeed, it is challenging to answer the questions of whether there are switchers and what types of properties are switching. It is difficult to gather a comprehensive data set on both long-term and short-term rental hosts. Even if the data are collected, one cannot identify the actual potential switchers by directly examining the observed hosts' decisions; a structural model on the hosts' decisions is required. Specifically, it is not appealing to take the observed data and assume, without modeling the hosts' decisions, that an observed "full-time" ("part-time") Airbnb listing always implies cannibalization (market expansion). First, if hosts list all year on Airbnb, this does not necessarily mean that they are switchers from the long-term rental market. They could have chosen to keep their properties vacant without Airbnb if their costs (revenues) of long-term rental were high (low). Second, if hosts list part of the year on Airbnb, it does not necessarily mean that the properties are not available for the rest of the year and are not switchers from long-term rentals. Hosts may choose to list for shorter periods if the Airbnb profit is large enough to allow them to list part time and still earn more than listing in the long-term rental market. Overall, researchers must systematically model the hosts' revenue-cost trade-offs to identify switchers. A structural model allows researchers to simulate the counterfactual scenario without Airbnb and compare it with the scenario when Airbnb is present, which are required to draw conclusions about the actual switchers.

Furthermore, a structural model is required to evaluate the effectiveness of existing rental regulations. To simulate hosting behaviors under various regulations in counterfactual scenarios, one needs to model the individual hosts' decisions and recover their underlying trade-offs. In addition, the prices, occupancy rates, and supply of housing units in the counterfactuals can differ from observed ones. We need to allow them to endogenously change and solve for new equilibrium outcomes. However, existing studies mostly provide descriptive analysis or conduct regression analysis, which do not allow for counterfactual analyses to evaluate policy impacts.

We fill the gap and contribute to the literature on Airbnb and rental housing market by building a structural model of hosting behaviors. To the best of our knowledge, we are the first to systematically and formally model hosts' decisions and to recover the underlying trade-offs. This framework allows us to conduct counterfactual analysis to identify actual switchers and examine policy impacts.

Existing studies primarily focus on Airbnb's impact on housing and rental prices in a particular city using descriptive or regression analysis. For example, Lee (2016) and Gurran and Phibbs (2017) provide descriptive analyses of Airbnb and the rental housing market in Los Angeles and Sydney, Australia, respectively. Horn and Merante (2017) find that a one-standard-deviation increase in Airbnb listings is associated with an increase in asking rents of 0.4% in Boston. Sheppard and Udell (2018) find that doubling the total number of Airbnb listings within 300 meters of a house is associated with an increase in house prices of 6% to 9% in New York City. Marketing researchers have also recently contributed to this topic. Barron, Kung, and Proserpio (2021) use a comprehensive data set covering the U.S. and find that a 1% increase in Airbnb listings leads to a 0.018% increase in rents and a 0.026% increase in house prices. These studies focus on how housing and rental prices changed after the introduction of Airbnb and do not directly address the switching behavior, the cause of changes in housing and rental prices. We formally model the hosts' supply choices. The structural model allows us to identify actual switchers by simulating the counterfactual scenario without Airbnb. We find that Airbnb mildly reduces long-term rental supply, which is consistent with findings in the literature that rental prices increased due to Airbnb. We also obtain a novel set of findings on switching behaviors across heterogeneous hosts. In particular, we find that affordable units experience a larger reduction in rental supply but have a lower fraction of switchers. These results have not been documented before and have strong policy implications for affordable housing.

In terms of the effectiveness of existing policies, existing literature on the topic is rare and adopts regression analysis. Koster et al. (2019) apply a panel regression-discontinuity design and find that the adoption of home sharing ordinances reduced housing prices by 3% and rents by 3% in Los Angeles. We use structural models to analyze individual hosts' decisions and simulate their behaviors under various counterfactual policy scenarios. We leverage data on a variety of cities and show that there is significant heterogeneity across cities, which is helpful for localized policy making. For example, we find that cities where Airbnb is more popular experience a larger reduction in the rental supply; however, these cities do not necessarily have a larger percentage of switchers. We also show that imposing a linear tax is more desirable than limiting the number of days a property can be listed.

More broadly, our paper contributes to the literature on how the sharing economy affects traditional industries and incumbent firms. For example, ride-sharing services affect the earnings of taxi drivers (Berger, Chen, and Frey 2018), automobile ownership (Gong, Greenwood, and Song 2017), alcohol-related motor vehicle fatalities (Greenwood and Wattal 2017), and local entrepreneurial activity (Burtch, Carnahan, and Greenwood 2018). On the subject of Airbnb, in a pioneering work, Zervas, Proserpio, and Byers (2017) study the impact of Airbnb's entry on hotels in Texas and find that Airbnb mildly cannibalizes hotels, with lower price hotels being the most affected. Li and Srinivasan (2019) study how Airbnb's flexible supply changes the way in which the industry accommodates seasonal demand and how incumbent hotels with fixed capacity should respond.

Our work also relates to the stream of literature on supply choices in the sharing economy. Zhang, Mehta, Singh, and Srinivasan (2018) model Airbnb hosts' decisions regarding whether to operate or block listings along with listing quality decisions (e.g., image quality in the listing description and host service effort). Li, Moreno, and Zhang (2016) study Airbnb hosts' pricing decisions and find that a substantial number of Airbnb hosts are unable to optimally set prices. We contribute to the literature by studying property owners' decisions regarding whether and how long to list on Airbnb.

Finally, our paper contributes to the literature on how the sharing economy affects marketing mix decisions (e.g., product choice, pricing, and distribution channels). Jiang and Tian (2018) study sharing-economy-enabled collaborative consumption and find that when a firm strategically chooses its retail price, consumers' sharing of products with high marginal costs is a win-win situation for both firm and consumers. Tian and Jiang (2017) study how consumer-to-consumer product sharing affects the distribution channel and find that the sharing market tends to increase the retailers' share of the gross profit margin in the channel. Dowling et al. (2019) study two common pricing strategies in car sharing services, pay-per-use and flat-rate pricing. They find a prevalent and time-persistent pay-per-use bias because of an underestimation of usage, a preference for flexibility, and the influence of physical context (e.g., weather). They suggest that the pay-per-use bias may be the prevalent tariff choice bias in the sharing economy.

3 Data

3.1 Data Description

The two main data sets used in this study are the 2015 and 2017 American Housing Survey (AHS) and Airbnb listings data for 9 representative metropolitan areas.[8] First, the AHS is the most comprehensive longitudinal national housing survey in the U.S. that gathers detailed property-level data on properties in metropolitan areas. It consists of a sample of representative properties that are scientifically selected to represent all housing units. Each observation includes a housing unit, its property characteristics (e.g., number of bedrooms and bathrooms, amenities, property type), occupant demographics (e.g., age, education, income, gender, marital status), tenure information (whether the unit is owner-occupied, renter-occupied, or vacant) and, if applicable, rent.[9] Each observation also includes a sampling weight, which is designed to extrapolate the sample to the full population of housing units. We use these sampling weights to present summary statistics and conduct analyses throughout the paper. As the survey is conducted biennially, we utilize the most recent two years' data at the time of this study. These two years also have a stronger Airbnb presence than the previous years as Airbnb continues to grow over time. We focus on the properties that are rented or vacant because they are potentially available for listing on either the long-term rental market or Airbnb and are thus relevant to our study.

The second data set contains information on every Airbnb property listed on Airbnb in 2015 and 2017 collected by AirDNA, a third-party company that specializes in data collection and analysis. Each property record contains monthly performance information such as the number of days available for booking, average daily rate, and occupancy rate. It also includes over 20 property characteristics such as location (zip code); property type (e.g., house, apartment); listing type (entire place or private/shared room); number of bedrooms and bathrooms; and amenities such as kitchen appliances, air conditioning, heating, washer, dryer, fireplace, and parking space. We also collect data on when a property is first listed on Airbnb to distinguish between no listing and a new listing.[10] In the 9 representative metro areas, there were 169,338 properties listed on Airbnb in 2015 and 252,459 properties in 2017.

Combining the two data sets provides a comprehensive data set on properties that are potentially available

[8] The U.S. Office of Management and Budget (OMB) refers to a metropolitan area as a core based statistical area (CBSA), which corresponds to an urbanized core area containing a substantial population and its adjacent communities having a high degree of economic and social integration with that core. For convenience, we denote a metro area by its principal city in the CBSA (e.g., New York for New York-Newark-Jersey City, NY-NJ-PA).

[9] The survey asks ex post questions about the use of the property "in the past 12 months", so the tenure information reflects the actual usage of the property.

[10] For example, if a property was first listed in February 2015, we exclude January 2015 when estimating the host's second-stage decision of how many days to list in a month because zero days listed in January 2015 is due to not have yet having joined Airbnb instead of choosing not to list.

for listing in the selected area.[11] A property is listed either on Airbnb (units in the Airbnb data set), the long-term rental market (rented units in the AHS data set), or neither (vacant units in the AHS data set). Hereafter, we refer to keeping the property vacant as the outside option. We distinguish between two types of units that choose the outside option, "vacant full year" and "vacant partial year", which correspond to units that are kept vacant for the full year and units that are kept vacant for part of the year due to occasional self-use in the AHS data set.

We focus on three sets of covariates in the empirical analysis: property characteristics, demographics, and market characteristics. The property characteristics are available at the property level in both the AHS data and the Airbnb data. Demographic information is available for each property in the AHS but not for the Airbnb listings. We collect zip-code-level demographics from the American Community Survey (ACS) and impute the host demographics for the Airbnb properties using the local zip-code-level demographics. The metro area characteristics include metro-area-level population, density, employment and wage information in the accommodation industry from the ACS data and mortgage affordability information from the Zillow Mortgage Affordability Index. We also collect data on an additional set of metro-area-level variables that serve as covariates in the estimation of hosts' choices and instruments in the hedonic regressions of revenues. These variables include the rent-to-own ratio, unemployment rate, number of air passengers to the city, Airbnb regulation score, Airbnb history, and Google search index for Airbnb. The rent-to-own ratio and unemployment rate are collected from the ACS. The number of air passengers to the city is from the T-100 Market (All Carriers) database published by the Bureau of Transportation Statistics.[12] Airbnb regulation score, which measures how friendly city policies are to short-term rentals, is published by the R Street Institute.[13] Airbnb history, measured by the time since Airbnb reached 10% of the total rooms supplied by hotel and Airbnb in a city, is computed using our Airbnb data set and the hotel data from tourism-related

[11] Note that the properties in the Airbnb data set can overlap with the properties in the AHS data set. We cannot perfectly distinguish whether an AHS property is listed on Airbnb because the observed characteristics do not allow us to perfectly link a property in the Airbnb data set to a property in AHS; the AHS data set intentionally removes information that allows for identification of a property. Nevertheless, we use information in AHS that can potentially indicate listing on Airbnb and remove those overlapping units so that there is no double-counting issue. Specifically, Airbnb has two types of properties: private room listings (i.e., owners live with the guests) and entire place listings (i.e., owners do not live in the properties). First, the private room Airbnb listings may overlap with owner-occupied AHS units. However, double-counting is not a concern here because owner-occupied AHS units are not included in our analysis. Second, the entire place Airbnb listings may overlap with vacant units in the AHS data set because AHS classifies housing units as vacant if they are unoccupied or occupied by anyone who is not the usual resident (such as an Airbnb guest). To remove this type of overlapping unit, we use a categorical variable in AHS that indicates how many nights a vacant property was rented out in the past year. There are three categories, namely, "0 to 2 nights", "3 to 7 nights", and "8 or more nights", each accounting for 91.1%, 0.23%, and 8.67% of the vacant properties, respectively. Intuitively, those rented for "3 to 7 nights" and "8 or more nights" are possibly rented on Airbnb and overlap with the entire place Airbnb listings. We also find that the number of such units in AHS is comparable to the number of entire place listings in the Airbnb data set. Therefore, we remove those vacant units that were rented for "3 to 7 nights" and "8 or more nights" from the AHS data set and combine the remaining vacant and rented AHS units with the Airbnb data set. The combined data set no longer contains overlapping properties and is used for our analysis. Besides removing overlapping units, the approach of identifying overlapping units also allows us to identify Airbnb listings in the AHS data set and present switching patterns among long-term rental, Airbnb, and the outside option within the AHS data set. We present the details in the online appendix.

[12] See https://www.transtats.bts.gov/DatabaseInfo.asp?DB_ID=111.

[13] See https://www.rstreet.org/wp-content/uploads/2016/03/RSTREET55.pdf.

Table 1: Summary Statistics by Airbnb, Long-Term Rental, and Outside Option

	Airbnb	Long-term Rental	Vacant Full Year	Vacant Partial Year
2015: Number of Units	155,725	8,481,448	685,332	251,240
2015: Proportion (%)	1.63	88.59	7.16	2.62
2017: Number of Units	221,730	8,409,056	603,665	233,810
2017: Proportion (%)	2.34	88.81	6.38	2.47
Number of Bedrooms	1.31 (0.87)	1.97 (0.96)	2.40 (1.06)	2.31 (1.04)
Number of Bathrooms	1.26 (0.59)	1.68 (1.17)	2.37 (1.35)	2.66 (1.31)
Apartment (%)	74.68 (43.48)	72.15 (44.83)	42.09 (49.39)	43.93 (49.68)
Kitchen (%)	90.77 (28.94)	99.14 (9.22)	98.65 (11.56)	96.66 (17.97)
Air Conditioning (%)	80.48 (39.63)	87.74 (32.79)	69.40 (46.10)	84.98 (35.76)
Heating (%)	87.22 (33.37)	99.37 (7.93)	97.88 (14.43)	96.08 (19.43)
Washer (%)	61.56 (48.65)	46.50 (49.88)	47.63 (49.96)	63.34 (48.24)
Dryer (%)	59.63 (49.06)	43.83 (49.62)	46.87 (49.92)	62.13 (48.55)
Fireplace (%)	10.91 (31.18)	11.20 (31.54)	19.08 (39.31)	13.75 (34.48)
Parking Space (%)	40.56 (49.10)	32.14 (46.70)	46.73 (49.91)	50.72 (50.04)
Private or Shared Room (%)	42.73 (49.47)			
Airbnb Daily Price ($)	148.72 (102.76)			
Airbnb Occupancy Rate (%)	31.20 (37.56)			
Monthly Rent ($)		1,263.74 (593.36)		

Note: Standard deviations are shown in parentheses. The numbers of long-term rental and vacant units in the table are extrapolated using sampling weights in the AHS data set. Similarly, the characteristics of the long-term rental and vacant units in the table are weighted averages using the sampling weights in the AHS data set.

reports and articles.[14] Lastly, Google search index for Airbnb is downloaded from Google and measures the number of Google searches for the term "airbnb" in a particular year and month. We normalize it to have a value of 100 at the peak month during the sample period.

3.2 Data Patterns

In this subsection, we describe the observed data patterns that motivate our empirical model specifications. In particular, we present the percentage of Airbnb, long-term rental, and outside option units, which relates to the first-stage decision of whether to list, and the listing patterns for the Airbnb units, which relate to the second-stage decision of how many days to list.

Table 1 presents the percentage of Airbnb, long-term rental, and outside option (vacant full year and vacant partial year) units by year and the summary statistics of properties choosing each option. In 2015, 1.63% of the property owners chose Airbnb and 88.59% chose long-term rental; 7.16% of properties were vacant for the full year, and 2.62% were vacant for part of the year. These numbers changed to 2.34%, 88.81%, 6.38%, and 2.47%, respectively, in 2017 as the number of Airbnb properties increased by nearly 50% from 2015 to 2017. We find that the Airbnb units have comparable property characteristics to the long-term

[14]See, for example, https://washington.org/dc-information/washington-dc-facts.

rental units. For example, both have smaller numbers of bedrooms and a larger proportion of apartment units than the outside option properties. This suggests that properties on Airbnb and in the long-term rental market may come from the same pool.

We further examine the listing patterns of properties on Airbnb. Property owners choose the dates when the property is available for booking (i.e., listed) or blocked from accepting reservations (i.e., not listed). We find that the listing pattern is heterogeneous across hosts and also across months within a host. Figure 1 plots the monthly number of days listed for two representative Airbnb properties. We find that hosts often choose not to list at all for a particular month. If a property is listed, it is more likely to be listed for the full month than for only part of the month. This is also supported by the histogram of the number of days listed in a month (Figure 2). The histograms for both 2015 and 2017 show a bimodal pattern with the two modes at "no listing" and "full listing". In addition, we find that hosts are more likely to list their properties longer in 2017 than in 2015.

We also explore the total number of days in a year that a property is listed on Airbnb, as the total revenue generated per year is more informative when compared with long-term rentals. Figure 3 shows the histogram of the percentage of days that a property is available for booking by year. In 2015, 51.7% of the properties are listed for less than half of the year. These "part-time" Airbnb hosts may list their properties only when they are not utilizing the property, such as when they are away on vacation. By contrast, some properties are listed most of the time. The data show that 33.5% of the observations are listed for more than 70% of the year, 26.2% are listed for more than 80% of the year, and 18.0% are listed for more than 90% of the year. Some of these properties may have been in the long-term rental market had Airbnb not been available. The listing pattern in 2017 shows a very similar pattern, with a slight shift to the right (i.e., longer listings).

3.2.1 Heterogeneity

The data patterns vary by metro area, property characteristics, and demographics. We present the data patterns averaged across years in this subsection, as they do not qualitatively change over time. Table 2 and Figure 4 show the observed percentages of Airbnb, long-term rental, and outside option units by metro area, number of bedrooms, and age group. First, these percentages vary significantly across metro areas. The percentage of Airbnb properties ranges from 0.26% in Detroit to 3.46% in San Francisco. The top three metro areas with the highest proportion of Airbnb properties are San Francisco, New York, and Miami. Second, the percentage of units choosing each option differs by property characteristics. As the number of bedrooms increases, the proportions of Airbnb properties and long-term rental properties both decrease in general, except the proportion of Airbnb increases for units with 4 or 5+ bedrooms. Third, the

Figure 1: Representative Airbnb Listing Patterns

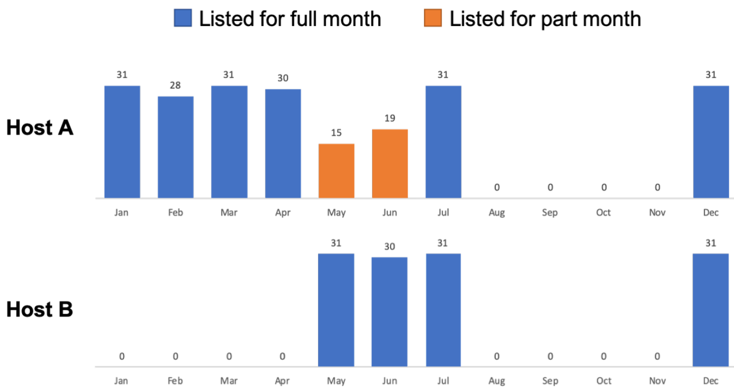


Figure 2: Histogram of Monthly Number of Days Listed

(a) 2015 (b) 2017

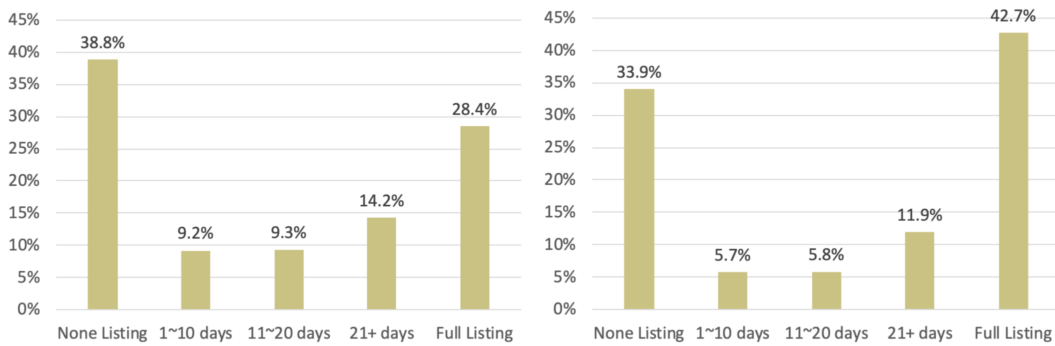


Figure 3: Histogram of Percentage of Days Listed in Each Year

(a) 2015 (b) 2017

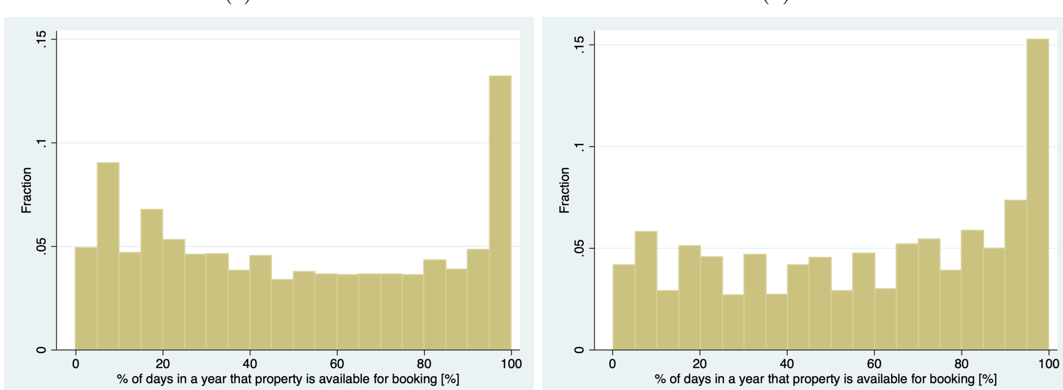


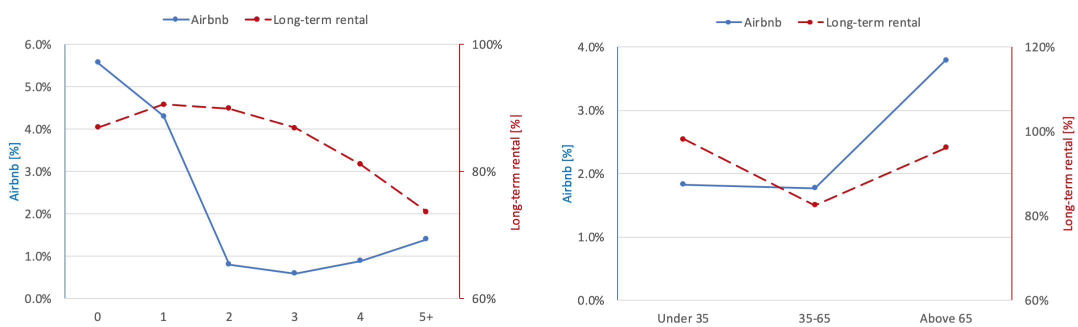
Table 2: Percentage of Units: By Metro Area

Metro Area	# Units	Percentage of Units [%]			
		Airbnb	Long-term Rental	Vacant Full Year	Vacant Partial Year
Boston-Cambridge-Newton, MA-NH	1,222,478	2.31	92.46	3.90	1.33
Chicago-Naperville-Elgin, IL-IN-WI	2,354,125	1.06	90.04	8.16	0.74
Dallas-Fort Worth-Arlington, TX	1,928,557	0.48	95.47	3.41	0.65
Detroit-Warren-Dearborn, MI	1,004,684	0.26	84.57	13.99	1.18
Miami-Fort Lauderdale-West Palm Beach, FL	2,062,516	2.46	72.16	15.98	9.40
New York-Newark-Jersey City, NY-NJ-PA	6,353,294	2.73	90.45	4.96	1.86
Phoenix-Mesa-Scottsdale, AZ	1,244,430	0.93	87.02	5.66	6.39
San Francisco-Oakland-Hayward, CA	1,352,516	3.46	91.84	3.74	0.97
Washington-Arlington-Alexandria, DC-VA-MD-WV	1,519,406	1.97	91.49	5.08	1.47

Figure 4: Percentage of Units by Property Characteristics and Demographics

(a) By Number of Bedrooms

(b) By Age Group



percentages of Airbnb units and long-term rental units first decrease with age and then significantly increase for seniors aged over 65, especially for Airbnb units. This is consistent with Airbnb's report that seniors are the fastest-growing demographic of Airbnb hosts.[15]

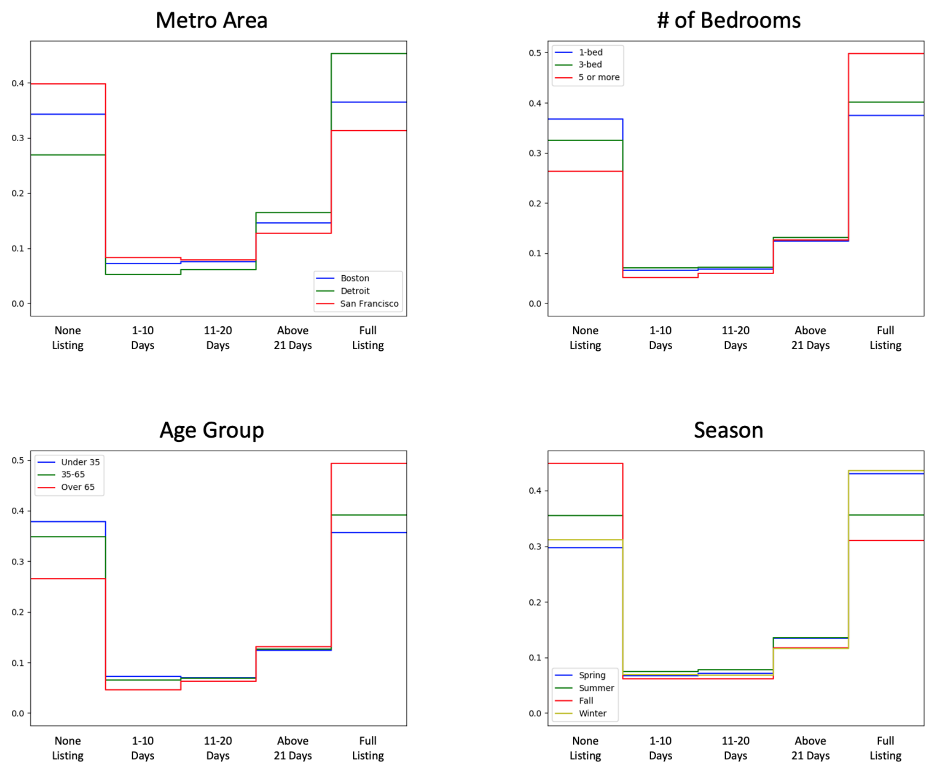
We also find that the Airbnb listing behavior varies by metro area, property characteristics, demographics, and season. Figure 5 shows a histogram of the number of days available for booking in a month by metro area, number of bedrooms, age, and season. Each observation represents a property-month combination. The overall bimodal pattern in Figure 2 holds for all subgroups, with variations across subgroups.

4 Model Setup

Property owners make endogenous decisions on whether and how long to list their properties based on cost-benefit trade-offs. Their decisions can be further affected by exogenously determined availability. In practice, one major reason for hosts to rent out their properties on Airbnb is to earn some extra money while they

[15]See https://www.airbnbcitizen.com/seniors-airbnbs-fastest-growing-most-loved-demographic/

Figure 5: Monthly Number of Days Listed by Metro Area, Property Characteristics, Demographics, and Season



are away (e.g., when they are on vacation).[16] These hosts cannot list on Airbnb when they need to live in the property (e.g., when they are working or studying); in this case, the decision not to list in a month is due to availability, not cost-benefit trade-offs. In general, the observed hosting decisions are a result of both the endogenous decisions based on cost-benefit trade-offs and the exogenously determined host availability. We need to distinguish between the case in which a host chooses not to list because of costs and benefits and the case in which a host cannot list due to availability reasons.

We model the exogenous availability of hosts by categorizing the properties into two types. The first type is available for rent for the full year (hereafter, "fully available" type); the property owner does not need the property for self-use at all in a year. The second type is available for rent only for some part of the year (hereafter, "partially available" type); the property owner may need to use the property for some part of the year. The availability type determines the choice set of the property owner. For fully available type, the property owners select the use of their properties among three options: (1) Keep the property vacant without listing it on any market. (2) Rent on the long-term rental market during the next 12 months with some cost. (3) Rent on Airbnb with some cost. For the partially available type, the property owners

[16]See https://www.cnbc.com/2019/07/03/is-running-an-airbnb-profitable-heres-what-you-need-to-know.html.

cannot choose the long-term rental option and only have options (1) and (3). Distinguishing between the two availability types is necessary to obtain unbiased estimates of hosting costs and results on switching and market expansion.[17]

Given the exogenous availability types, property owners make endogenous decisions in two stages. In the first stage, at the beginning of each year, they select the use of their properties given their availability type and the corresponding options. In the second stage, if they choose Airbnb, they decide the number of days to list on Airbnb in each month. If they choose long-term rental or the outside option, there are no further decisions to make, as long-term rental hosts are bound by long-term leases during the lease period. This two-stage setup represents the fact that property owners usually decide the use of their property at the year level and the number of days to list on Airbnb at the month level.

Property owners make decisions to maximize their profits given their expectations about the rent and occupancy rate they can obtain in the long-term rental market and the price and occupancy rate they can obtain on Airbnb. We assume that the expectation is formed using a hedonic approach, which we detail in Section 4.4. We normalize the profit from the outside option to zero.

In addition to the revenues, property owners consider the costs of renting on the long-term rental market versus Airbnb.[18] The costs can include both *tangible* costs (e.g., property maintenance) and *intangible* costs (e.g., hassle from dealing with renters, living with Airbnb travelers). Specifically, in the first stage, property owners may incur the cost of long-term rental and the fixed cost of Airbnb hosting. The cost of long-term rental may include fees, taxes, insurance, and maintenance costs. The fixed cost of Airbnb hosting may include the psychological cost of renting out property to transient guests, preparing property photos and descriptions, and preparing furnishings and amenities. In the second stage, Airbnb hosts may incur variable costs during the days they list their properties on Airbnb. These costs may include responding to guest inquiries and reservations, checking guests in and out, maintaining the property, and paying utility bills. We discuss how the cost functions are constructed and estimated in the following sections.

We make several assumptions. First, we assume that the set of potential properties that can be rented

[17]To see why, suppose we do not distinguish between the two types and allow all hosts to choose among Airbnb, long-term rental, and the outside option in the model. If property i is actually the "partially available" type and is listed on Airbnb in the data, the model that forces all hosts to choose among all three options will conclude that property i's Airbnb profit must be higher than its long-term rental profit. However, this is not necessarily true in reality because the fact that property i is not listed on the long-term rental market is due to availability reasons and not because of cost-revenue trade-offs; property i's host can only compare profits from Airbnb versus vacant. Therefore, for a "partially available" type property on Airbnb, a model that forces all hosts to choose among all three options will overestimate its Airbnb profit and underestimate its Airbnb hosting cost. Distinguishing between the two types is also important for analyzing switching and market expansion, which we detail in Section 7.2.

[18]We need to model the costs in addition to the revenues because the observed revenues alone cannot explain the observed hosting behaviors. For example, we observe that properties with more bedrooms have higher revenues on either the long-term rental market or Airbnb, suggesting that it is more beneficial for the hosts to rent out these properties. However, by contrast, we observe that properties with more bedrooms have lower probabilities of listing on either the long-term rental market or Airbnb, as shown in Figure 4. It means that revenue itself cannot rationalize the hosting decisions in the data. We need to incorporate cost-side components in the hosts' decision problem. Our cost-side estimates show that properties with more bedrooms have higher hosting costs, which can explain why these properties are less likely to be listed on either market in the data.

or vacant is fixed as exogenously given in the data. We do not consider the case in which hosts purchase or build new properties because of the introduction of Airbnb.[19] Second, we assume away the case in which long-term rental tenants sublet on Airbnb because we do not observe whether an Airbnb listing is from a sublease or not. This type of case may be relatively rare, as lease agreements often include clauses that prohibit sublets. Services such as SubletAlert.com and SubletSpy also help landlords find tenants who have violated the agreement. Our model focuses on the property owners' decisions and does not consider the renters' decisions to sublet. Future research may extend the proposed model to incorporate cases in which tenants sublet on Airbnb if such data are available and such cases become more common.[20] Third, we model the long-term rental choice as a yearly decision because the long-term rental lease is usually one year long in practice. Therefore, the model does not allow the host to choose long-term rental for part of the year and Airbnb for the rest of the year.

4.1 Second Stage: Continuous Decision of Listing on Airbnb

We first describe the model setup for the second-stage decision, because the profits from the second stage are nested into the first-stage decision and property owners must form expectations about the second stage before making first-stage decisions. Note that although in the data we observe the second-stage monthly decisions only for Airbnb properties, in the model we need to solve for the optimal second-stage monthly decisions for every property. This is because hosts in the model choose among Airbnb, long-term rental, and vacant options in the first stage. To make this decision, they need to formulate and compare the expected profits from each option, regardless of which option they chose in the data. The expected profits of the Airbnb option are calculated by summing over the expected monthly Airbnb profits in the second stage. Therefore, we need to solve for the second-stage monthly decisions for each host in the model.

In the second stage, conditional on choosing Airbnb in the first stage, the owner determines the number of days to list the property on Airbnb. Let s_{it} denote the number of days that property i is listed on Airbnb in month t. The owner chooses $s_{it} \in [0, \bar{s}]$, where the total number of days in each month $\bar{s}$ serves as the upper bound.[21] In the counterfactual analysis, we allow $\bar{s}$ to reflect the maximum listing length imposed by

[19]New properties built or purchased because of Airbnb count towards the market expansion effect of Airbnb; they would not have been listed on the long-term rental market without Airbnb. Allowing for these new properties will increase the size of the market expansion effect, so our estimated size in this paper can serve as a lower bound in this case.

[20]In the case where renters of long-term rental properties sublease on Airbnb, these properties are still part of the long-term rental supply as property owners still rent these properties to renters on the long-term rental market. Therefore, the property owners are not switchers from long-term rental to Airbnb and do not count towards cannibalization. However, the renters earn additional income on Airbnb; they would not have had this additional income source without Airbnb. Therefore, the renters are non-switchers and count towards the market expansion effect of Airbnb. Overall, considering renter sublease does not affect the size of cannibalization, while it increases the size of market expansion. Our estimated size of cannibalization is not affected while our estimated size of market expansion can serve as a lower bound in this case.

[21]In practice, there are government regulations that limit the maximum number of days on which a property can be listed on Airbnb. These regulations were imposed after our sample period ended; therefore, we do not account for them as $\bar{s}$ in our model estimation. The only exception is the Airbnb law in San Francisco, which went into effect on February 1, 2015

government regulations. In this section, we derive the model by allowing s_{it} to take any value between 0 and $\bar{s}$ for illustrative purposes. We account for the fact that s_{it} is an integer when we estimate the model and detail how we treat the integer issue in the online appendix.

The optimal monthly number of days to list is chosen to maximize the monthly profit from Airbnb for property i in month t:

$$\Pi_{it}^{A}(s_{it}) = p_{it}^{A}\phi_{it}^{A}s_{it} - c_{it}^{Av} \cdot \bar{s}\left(\exp\left(\frac{s_{it}}{\bar{s}}\right) - 1\right) \tag{1}$$

where p_{it}^{A} and ϕ_{it}^{A} are the *expected* average daily price and occupancy rate of property i. We discuss how the expectations are formed in Section 4.4. Here, c_{it}^{Av} is the heterogeneous variable cost of Airbnb hosting per day, to be parameterized later. The first term of the profit function represents the revenue, which is proportional to the number of days booked. The second term represents the cost, which increases with the number of days listed. Note that the profit is zero if the property is not listed, i.e., $\Pi_{it}^{A}(0) = 0$. Taking the derivative with respect to s_{it}, the optimal number of days to list is as follows:

$$s_{it}^{*} = \min\left\{\bar{s} \cdot \ln\left(\frac{p_{it}^{A}\phi_{it}^{A}}{c_{it}^{Av}}\right), \bar{s}\right\} \tag{2}$$

where the min operator accounts for the range of $s_{it} \in [0, \bar{s}]$. The solution suggests that the number of days to list on Airbnb is an endogenous function of the ex ante expected revenue $\left(p_{it}^{A}\phi_{it}^{A}\right)$ and heterogeneous cost of Airbnb hosting $\left(c_{it}^{Av}\right)$. It has the desirable property such that the larger the revenue-to-cost ratio is, the longer the property owner will choose to list on Airbnb.

The variable cost of Airbnb hosting for property i in month t is formulated as follows:

$$c_{it}^{Av} = \bar{c}^{Av} + \beta^{Av}X_{it}^{Av} + \xi_{mt}^{Av} + \epsilon_{it}^{Av} \tag{3}$$

where $\bar{c}^{Av}$ is the baseline cost, X_{it}^{Av} are observed characteristics that affect the cost in a continuous way, ξ_{mt}^{Av} is a market-specific time variable that captures any remaining time-varying unobservables, and ϵ_{it}^{Av} is an independently normally distributed idiosyncratic shock with mean zero and standard deviation σ_2. Specifically, X_{it}^{Av} includes property characteristics (number of bedrooms/bathrooms/amenities, listing type), host demographics (age, education, income, marital status, gender), and a set of metro-area-level characteristics that relate to the cost of hosting.[22] The metro-area-level characteristics include population, density,

and restricts short-term rentals to a maximum of 90 days per year. However, the law was not strictly enforced, as the data show that 25% of the listings were listed for more than 90 days during the 9-month period from February 2015 (when the law went into effect) to October 2015. In fact, the lack of strict law enforcement was also reported during this time period. See https://www.sfchronicle.com/business/article/Airbnb-loses-thousands-of-hosts-in-SF-as-12496624.php.

[22]The host demographics are captured by dummy variables, one for each demographic group. For example, there are three age groups, "under 35", "35 to 65", and "over 65", which are captured by three dummy variables. For AHS properties, we observe individual host demographics, so the demographic dummy variables take the value of 0 or 1. For Airbnb properties, we do not

mortgage affordability index, average wage and employment in the accommodation industry (measured as the percentage of the population who work in the accommodation industry), and Airbnb regulation score (measures how friendly city regulations are to short-term rental). Intuitively, a large property may be more costly to maintain and induce a larger variable cost of hosting. The hosting cost can vary by host demographics and across seasons even for the same host. Hosts in cities with more employees and lower wages in the accommodation industry may find it easier to obtain room maintenance services and thus have a lower variable cost of hosting. Hosts in cities with more favorable Airbnb regulations may face a lower variable cost of hosting. The level of mortgage pressure can further impact how long the hosts would like to list their property. Finally, the market-specific time variable is specified as $\xi_{mt}^{Av} = \xi_t + \xi_0^{Av} \cdot 1\{T = 2017\} + \xi_1^{Av} \cdot \left(T - T_m^0\right)$, where ξ_t are season fixed effects (spring, summer, fall, winter) and T_m^0 represents the year when Airbnb reached 10% of the total rooms supplied by hotels and Airbnb in a city. The first component captures any monthly unobservables that vary across seasons. The second component captures any yearly unobservables that affect all metro areas (e.g., because of Airbnb's national marketing) relative to those in the baseline year 2015. The third component captures any market-specific time trend related to Airbnb history or how long Airbnb has been present in a city. For example, Airbnb may be better received in markets where it has been present longer.

We summarize the covariates that enter the Airbnb variable cost (c_{it}^{Av}) in Column 3 of Table 3a.

Derivation of the second-stage probability. Let $\Pr(s_{it} \mid \mathcal{X}_i)$ denote the second-stage choice probabilities, where $\mathcal{X}_i$ contains all host demographics, metro area and property characteristics that affect the costs and revenues of host i. We can construct $\Pr(s_{it} \mid \mathcal{X}_i)$ based on the feasible range of the normally distributed error term $\{\epsilon_{it}^{Av}\}$ in c_{it}^{Av} implied by the optimal choices in Equation 2:

$$\begin{aligned}
\Pr(s_{it} = 0 \mid \mathcal{X}_i) &= \Pr\left(\epsilon_{it}^{Av} > p_{it}^A \phi_{it}^A - (\bar{c}^{Av} + \beta^{Av} X_{it}^{Av} + \xi_{mt}^{Av})\right) \\
&= 1 - \Phi\left(\frac{1}{\sigma_2}\left(p_{it}^A \phi_{it}^A - (\bar{c}^{Av} + \beta^{Av} X_{it}^{Av} + \xi_{mt}^{Av})\right)\right) \\
\Pr(s_{it} = \bar{s} \mid \mathcal{X}_i) &= \Pr\left(\epsilon_{it}^{Av} < \frac{p_{it}^A \phi_{it}^A}{\exp(1)} - (\bar{c}^{Av} + \beta^{Av} X_{it}^{Av} + \xi_{mt}^{Av})\right) \\
&= \Phi\left(\frac{1}{\sigma_2}\left(\frac{p_{it}^A \phi_{it}^A}{\exp(1)} - (\bar{c}^{Av} + \beta^{Av} X_{it}^{Av} + \xi_{mt}^{Av})\right)\right)
\end{aligned}$$

where $\Phi(\cdot)$ is the CDF of the standard normal distribution. The derivation of $\Pr(s_{it} = s, 0 < s < \bar{s} \mid \mathcal{X}_i)$ accounts for the fact that the number of days listed s_{it} is an integer. We detail the derivation in the online appendix.

observe individual host demographics and impute them using the local zip-code-level demographics. The demographic dummy variables take the value of the percentage of a specific demographic group in the zip code. For example, the dummy variable "age under 35" takes the value of 30% if the host lives in a zip code where 30% of the population is under 35.

Note that we do not restrict c_{it}^{Av} to be nonnegative for mathematical reasons. The optimal number of days listed s_{it} can take values from 0 to $\bar{s}$. Allowing c_{it}^{Av} to take any real values guarantees that the probabilities of s_{it} taking each possible value sum up to 1, $\Pr(s_{it} = 0 \,|\, \mathcal{X}_i) + \Pr(0 < s_{it} < \bar{s} \,|\, \mathcal{X}_i) + \Pr(s_{it} = \bar{s} \,|\, \mathcal{X}_i) = 1$.[23] To interpret the value of c_{it}^{Av}, a lower value of c_{it}^{Av} suggests that the property is more likely to be listed longer. A negative value of c_{it}^{Av} suggests that the property is more likely to be listed for the full month. We also bound the monthly profit Π_{it}^{A} by $p_{it}^{A}\bar{s}$, which is the maximum profit that a listing can possibly generate.

4.2 First Stage: Discrete Decision of Where to List

In the first stage, property owners decide whether and where to list their properties given their availability types. The fully available property owners choose among long-term rental, Airbnb, and the outside option given the expected yearly profit from the second-stage decision for each option. Let d_{iT} denote the decision of property owner i in year T, and index the alternatives by superscripts A (Airbnb), R (long-term rental), and O (outside option). The fully available property owners solve the following problem:

$$
\begin{aligned}
&\max_{d \in \{A,R,O\}} \Pi_{iT}^{d} \\
&\qquad \Pi_{iT}^{A} = \sum_{t \in T} \left(E\left[\Pi_{it}^{A}(s_{it}^{*}) \right] \right) - c_{iT}^{Af} \\
&\qquad \Pi_{iT}^{R} = p_{iT}^{R} \phi_{iT}^{R} - c_{iT}^{R} \\
&\qquad \Pi_{iT}^{O} = 0
\end{aligned} \tag{4}
$$

The partially available owners solve a similar problem without the long-term rental option:

$$
\begin{aligned}
&\max_{d \in \{A,O\}} \Pi_{iT}^{d} \\
&\qquad \Pi_{iT}^{A} = \sum_{t \in T} \left(E\left[\Pi_{it}^{A}(s_{it}^{*}) \right] \right) - c_{iT}^{Af} \\
&\qquad \Pi_{iT}^{O} = 0
\end{aligned} \tag{5}
$$

Here, Π_{iT}^{d} represents the yearly profit from each alternative $d \in \{A, R, O\}$. The profit of the outside option

[23] Specifically, we can re-write the second-stage probabilities as functions of c_{it}^{Av}: $\Pr(s_{it} = 0 \,|\, \mathcal{X}_i) = \Pr\left(c_{it}^{Av} > p_{it}^{A}\phi_{it}^{A}\right)$, $\Pr(0 < s_{it} < \bar{s} \,|\, \mathcal{X}_i) = \Pr\left(\frac{p_{it}^{A}\phi_{it}^{A}}{\exp(1)} < c_{it}^{Av} < p_{it}^{A}\phi_{it}^{A}\right)$, $\Pr(s_{it} = \bar{s} \,|\, \mathcal{X}_i) = \Pr\left(c_{it}^{Av} < \frac{p_{it}^{A}\phi_{it}^{A}}{\exp(1)}\right)$. Given that s_{it} can take any value from 0 to $\bar{s}$, these three probabilities needs to sum up to 1. Allowing c_{it}^{Av} to be in the whole real line guarantees that the requirement is satisfied. However, if we restrict c_{it}^{Av} to be non-negative, the first two probabilities remain the same, while the third probability will be smaller than before because now $\Pr(s_{it} = \bar{s} \,|\, \mathcal{X}_i) = \Pr\left(0 < c_{it}^{Av} < \frac{p_{it}^{A}\phi_{it}^{A}}{\exp(1)}\right)$ and is smaller than $\Pr\left(c_{it}^{Av} < \frac{p_{it}^{A}\phi_{it}^{A}}{\exp(1)}\right)$. In this case, the sum of the three probabilities will be smaller than 1, which violates the requirement.

Table 3: Summary of Covariates

(a) Covariates

	Owner type	Cost		Revenue Hedonic regression			
	γ_{iT}	c_{iT}^{Af}	c_{it}^{Av}	p_{it}^{A}	ϕ_{it}^{A}	p_{iT}^{R}	ϕ_{iT}^{R}
Property characteristics		yes	yes	yes	yes	yes	yes
Demographics	yes		yes	yes	yes	yes	yes
Metro area characteristics	yes		yes	yes (metro-	yes (metro-	yes	yes
Season fixed effect			yes	year-month)	year-month)	(metro-year)	(metro-year)
Mortgage		yes	yes				
Wage and employment in accommodations industry		yes	yes				
Airbnb regulation score			yes				
Airbnb history		yes	yes	yes	yes		
Tourism (air passengers)				yes	yes		
Google search index for Airbnb				yes	yes		
Total Airbnb supply				yes	yes		
Airbnb price					yes		
Total rental supply						yes	yes
Rent							yes

(b) Data Description of Covariates

Covariate	Data Description
Property characteristics	Number of bedrooms/bathrooms/amenities, property type: house (dummy)
Demographics	Age 35-65, age over 65, high school education, bachelor's education, 50-100k income, over 100k income, male, and marital status never. *The baseline demographic group is age under 35, education below high school, income below 50k, female, and married.
Metro area characteristics	Population, density
Mortgage	Mortgage affordability index from Zillow
Wage and employment in accommodations industry	Average wage in the accommodation industry, percentage of the population who work in the accommodation industry
Airbnb regulation score	A score that measures how friendly city regulations are to short-term rental
Airbnb history	Time since Airbnb reached 10% of total rooms supplied by hotels and Airbnb in a city
Tourism	Number of air passengers to a city
Google search index for Airbnb	Number of searches for "airbnb" on Google
Total Airbnb supply	Number of days listed on Airbnb by units that are comparable to the focal property in the same city in a month
Airbnb price	Average daily price of the focal property on Airbnb in a month
Total rental supply	Number of units listed on the long-term rental market that are comparable to the focal property in the same city in a year
Rent	Rent of the focal property on the long-term rental market in a year

is normalized to zero. The profit of long-term rental comes from the ex ante *expected* yearly rent (p^R_{iT}) multiplied by the *expected* occupancy rate (ϕ^R_{iT}) minus the cost of long-term rental (c^R_{iT}). We discuss how the expectations are formed in Section 4.4. The profit of Airbnb comes from the sum of the ex ante monthly profit from Airbnb hosting $\left(\sum_{t\in T}\left(E\left[\Pi^A_{it}(s^*_{it})\right]\right)\right)$ minus the fixed cost of Airbnb hosting (c^{Af}_{iT}). The ex ante monthly profit from Airbnb hosting is obtained by substituting the optimal number of days to list in Equation 2 into Equation 1 and taking expectations over the error terms ϵ^{Av}_{it} in c^{Av}_{it}:

$$E\left[\Pi^A_{it}(s^*_{it})\right] = \left[\int_{-\infty}^{\infty} \Pi^A_{it}\left(s^*_{it}\right) f\left(\epsilon^{Av}_{it}\right) d\epsilon^{Av}_{it}\right] \tag{6}$$

We show in the online appendix how we compute the ex ante monthly profit, accounting for s_{it} being integers. Note that we are able to calculate $E\left[\Pi^A_{it}(s^*_{it})\right]$ for every host without observing the actual monthly decisions in the data. This is because the optimal number of days listed s^*_{it} and the ex ante monthly Airbnb profits $E\left[\Pi^A_{it}(s^*_{it})\right]$ are functions of the hosting costs and expected prices and occupancy rates. The hosting costs are functions of the observable characteristics as shown in Equation 3; the expected monthly prices and occupancy rates are functions of the observable characteristics as shown in Section 4.4. Therefore, s^*_{it} and $E\left[\Pi^A_{it}(s^*_{it})\right]$ are functions of the observable characteristics as well, which are observed for every property, regardless of whether the property is listed on Airbnb in the data. We can use the observed characteristics to compute s^*_{it} and $E\left[\Pi^A_{it}(s^*_{it})\right]$ for every host without observing their actual second-stage monthly decisions.

Property owners are heterogeneous in the fixed cost of Airbnb hosting and the cost of long-term rental. The cost of long-term rental for property i in year T is assumed to be $c^R_{iT} = \epsilon^R_{iT}$, where ϵ^R_{iT} is independently normally distributed with mean 0 (normalized to zero for identification reasons) and variance σ^2_1 and is independent of the second-stage error terms $\{\epsilon^{Av}_{it}\}$.

The fixed cost of Airbnb hosting for property i in year T is:

$$c^{Af}_{iT} = \bar{c}^{Af}_{\tau} + \beta^{Af} X^{Af}_{iT} + \xi^{Af}_{mT} + \epsilon^{Af}_{iT} \tag{7}$$

where $\tau = 1$ denotes the fully available type and $\tau = 2$ denotes the partially available type. The baseline cost $\bar{c}^{Af}_{\tau}$ can take different values for fully available owners ($\tau = 1$) and partially available owners ($\tau = 2$). Intuitively, the two types of owners can have different Airbnb fixed costs because their availability affects their psychological and tangible costs of adopting Airbnb. ξ^{Af}_{mT} is a market-specific time variable that captures any time-varying unobservables; ϵ^{Af}_{iT} is an idiosyncratic shock that is independently normally distributed with mean 0 and variance σ^2_1 and is independent of the second-stage error terms $\{\epsilon^{Av}_{it}\}$. The linear component X^{Af}_{iT} includes metro area characteristics (mortgage affordability index, average wage and employment in the accommodation industry) and property characteristics (number of bedrooms/bathrooms/amenities, property type). The market-specific time variable is specified as $\xi_{mT}^{Af} = \xi_0^{Af} \cdot 1\{T = 2017\} + \xi_1^{Af} \cdot (T - T_m^0)$, where T_m^0 represents the year when Airbnb reached 10% of the total rooms supplied by hotels and Airbnb in a city. The first component captures any yearly unobservables that affect all metro areas, and the second component captures any market-specific time trend related to Airbnb's history in a city.

Derivation of the first-stage probability. We can construct the first-stage choice probabilities $\Pr(d_{iT} | \tau_i, \mathcal{X}_i)$ based on the feasible range of the independently normally distributed error terms $\left\{\epsilon_{iT}^{Af}, \epsilon_{iT}^{R}\right\}$ in c_{iT}^{Af} implied by the optimal choices in Equations 4 and 5. Define $a_\tau \equiv \sum_{t \in T} E\left[\Pi_{it}^A(s_{it}^*) - c_{iT}^{Af} | \tau_i\right]$ and $r \equiv E\left(p_{iT}^R \phi_{iT}^R - c_{iT}^R\right)$. For the fully available hosts ($\tau_i = 1$), they choose among Airbnb, long-term rental, and the outside option and have the following choice probabilities:

$$
\begin{aligned}
\Pr(d_{iT} = O \,|\, \tau_i = 1, \mathcal{X}_i) &= \Pr\left(\epsilon_{iT}^{Af} > a_1, \epsilon_{iT}^{R} > r\right) = \left(1 - \Phi\left(\frac{a_1}{\sigma_1}\right)\right)\left(1 - \Phi\left(\frac{r}{\sigma_1}\right)\right) \\
\Pr(d_{iT} = R \,|\, \tau_i = 1, \mathcal{X}_i) &= \Pr\left(\epsilon_{iT}^{R} < r, \epsilon_{iT}^{R} - \epsilon_{iT}^{Af} < r - a_1\right) \\
&= \Phi\left(\frac{r}{\sigma_1}\right) - \int_{-\infty}^{r} \Phi\left(\frac{\epsilon^R - r + a_1}{\sigma_1}\right)\phi\left(\frac{\epsilon^R}{\sigma_1}\right) d\epsilon^R \\
\Pr(d_{iT} = A \,|\, \tau_i = 1, \mathcal{X}_i) &= \Pr\left(\epsilon_{iT}^{Af} < a_1, \epsilon_{iT}^{Af} - \epsilon_{iT}^{R} < a_1 - r\right) \\
&= \Phi\left(\frac{a_1}{\sigma_1}\right) - \int_{-\infty}^{a} \Phi\left(\frac{\epsilon^{Af} - a_1 + r}{\sigma_1}\right)\phi\left(\frac{\epsilon^{Af}}{\sigma_1}\right) d\epsilon^{Af}
\end{aligned}
$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the PDF and CDF of the standard normal distribution. The integrals in $\Pr(d_{iT} = R | \tau_i = 1, \mathcal{X}_i)$ and $\Pr(d_{iT} = A | \tau_i = 1, \mathcal{X}_i)$ are calculated using Gauss-Laguerre quadrature with 10 nodes. For the partially available hosts ($\tau_i = 2$), they choose between Airbnb and the outside option and have the following choice probabilities:

$$
\begin{aligned}
\Pr(d_{iT} = O \,|\, \tau_i = 2, \mathcal{X}_i) &= \Pr\left(\epsilon_{iT}^{Af} > a_2\right) = \left(1 - \Phi\left(\frac{a_2}{\sigma_1}\right)\right) \\
\Pr(d_{iT} = A \,|\, \tau_i = 2, \mathcal{X}_i) &= \Pr\left(\epsilon_{iT}^{Af} < a_2\right) = \Phi\left(\frac{a_2}{\sigma_1}\right)
\end{aligned}
$$

4.3 Owner Availability Types

In the data, we observe the owner availability types τ_i for properties that are on the long-term rental market and are kept vacant. Specifically, owners of units on the long-term rental market in the data are the fully available type because they are able to list the property for the full year. Owners of properties that are kept vacant for the full year are the fully available type, whereas owners of properties that are kept vacant for the some part of the year due to occasional self-use are the partially available type. However, we do not observe the owner availability types for properties on Airbnb in the data.[24] There are two exceptions: 1) properties that are listed every month throughout the year in the data must be the fully available type, as availability is a necessary condition for listing; 2) properties that are listed as a "private room" (instead of an "entire place") must be the partially available type because the hosts live with the guests in this case. Apart from these two cases, we do not know whether an Airbnb host is fully available or partially available.

For model estimation purposes, we adopt a probabilistic view on the availability type of Airbnb hosts in the data. The probability that an Airbnb property i is the fully available type ($\tau_i = 1$) in year T is

$$\Pr(\tau_i = 1) = \gamma_{iT} = \frac{\exp(\beta X_{iT})}{1 + \exp(\beta X_{iT})} \tag{8}$$

The probability that it is the partially available type is $\Pr(\tau_i = 2) = 1 - \gamma_{iT}$. Here, X_{iT} includes host demographics (age, education, income, marital status, gender), metro area characteristics (population and density), and a dummy for being a single bedroom. Intuitively, a host's availability can be related to who the host is, where the host lives, and what type of property the host has.

We summarize the covariates that enter owner availability type (γ_{iT}) and Airbnb fixed cost (c_{iT}^{Af}) in Columns 1 and 2 of Table 3a.

4.4 Expectation of Revenue

Property owners' decisions in Equations 1, 4, and 5 contain revenue information, i.e., rent, rental occupancy rate, Airbnb price, and Airbnb occupancy rate. We assume that property owners form expectations over these variables using a typical hedonic approach when making their first-stage decisions. Hedonic regression is a widely used method to estimate property value by decomposing a property's value into its constituent attributes and obtaining contributory values for each attribute (see Sirmans, Macpherson, and Zietz (2005) for a review on using hedonic models to estimate house prices). We use the hedonic approach because it offers the following three advantages. First, the hedonic model incorporates property heterogeneity, which allows us to construct expected revenues for each property in the data. It also parsimoniously captures how hosts set prices and how occupancy rates are determined in practice. Second, this approach allows us to obtain rent, rental occupancy rate, Airbnb price, and Airbnb occupancy rate regardless of how the units are utilized. In the data, we observe rent and rental occupancy only for properties that were listed on the long-term rental market in a year and observe Airbnb price and occupancy rate only for properties that were listed on Airbnb

[24]Note that one cannot conclude that Airbnb properties that are listed for some part of the year must be the partially available type. This is because the observed listing pattern is a result of both the endogenous decision of the hosts and the exogenous host availability type. A fully available host may choose to list for only part of the year because the costs exceed the benefits for the rest of the year.

in a year. However, the property attributes are observed for all properties. The hedonic model allows us to construct the expected rent and rental occupancy for properties listed on Airbnb and the expected Airbnb price and occupancy rate for properties listed on the long-term rental market. The underlying assumption is that properties with similar attributes will have similar revenues. Third, the hedonic approach allows us to generate counterfactual rent, rental occupancy, Airbnb price, and Airbnb occupancy under counterfactual scenarios, which we discuss in detail in Section 7.1. Li and Srinivasan (2019) adopt a similar approach by first estimating how prices and supply are determined in the data and using the estimates to generate new prices and supply in the counterfactual analysis.

The hedonic models of rent and rental occupancy for property i in market m in year T are

$$p_{iT}^{R} = \rho_0 + \rho_1 x_i^P + \rho_2 x_i^D + \rho_3 S_{imT}^{R} + \psi_{mT}^{Rp} + \varepsilon_{iT}^{Rp} \tag{9}$$

$$\phi_{iT}^{R} = \eta_0 + \eta_1 x_i^P + \eta_2 x_i^D + \eta_3 S_{imT}^{R} + \psi_{mT}^{Ro} + \eta_4 p_{iT}^{R} + \varepsilon_{iT}^{Ro} \tag{10}$$

where we regress the rent of property i in year T, p_{iT}^{R}, on property characteristics x_i^P, household demographics x_i^D, rental supply of comparable units in the metro area S_{imT}^{R} (measured as the number of units that are comparable to property i and choose to list on the long-term rental market), and metro-area-specific year fixed effects ψ_{mT}^{Rp}.[25] Here, m denotes the metro area to which property i belongs. The hedonic model of the rental occupancy ϕ_{iT}^{R} uses the same specification except it also includes rent as an additional regressor because the occupancy rate depends on the price. To run the rental occupancy regression, we supplement the original data set, which contains long-term rental properties (i.e., rented properties in the AHS data set), with data on properties that are for rent but not rented from the AHS data set.[26] We exclude outliers with rents below the 5th percentile and above the 95th percentile when running the regressions.

The hedonic models of Airbnb price and occupancy rate for property i in market m in month t are

$$p_{it}^{A} = \delta_0 + \delta_1 x_i^P + \delta_2 x_i^D + \delta_3 S_{imt}^{A} + \delta_4 x_{mt}^{A} + \psi_{mt}^{Ap} + \varepsilon_{it}^{Ap} \tag{11}$$

$$\phi_{it}^{A} = \gamma_0 + \gamma_1 x_i^P + \gamma_2 x_i^D + \gamma_3 S_{imt}^{A} + \gamma_4 x_{mt}^{A} + \psi_{mt}^{Ao} + \gamma_5 p_{it}^{A} + \varepsilon_{it}^{Ao} \tag{12}$$

where we regress the monthly logged average daily price of property i in month t, p_{it}^{A}, on property characteristics x_i^P, household demographics x_i^D, Airbnb supply of comparable units in the metro area S_{imt}^{A} (measured as the number of days listed by all units that are comparable to property i on Airbnb), Airbnb-related variables

[25] "Comparable" units are those with the same number of bedrooms. We conduct a robustness check by defining comparable units as those with the same numbers of bedrooms and bathrooms and obtain robust estimates. We keep the original definition because it produces a larger R-squared of the regressions.

[26] The average occupancy rate, or the fraction of rented properties among all for-rent (rented and for-rent but not rented) properties, is 91.9% in the data.

x^A_{mt}, and metro-area-specific year and month fixed effects ψ^{Ap}_{mt}. The market-specific year and month fixed effects can capture market-specific seasonality patterns in Airbnb prices. The Airbnb-related variables include tourism (measured as the number of air passengers to the city), Airbnb history (measured as the number of months since Airbnb reached 10% of the total rooms supplied by hotels and Airbnb in a city), and Google search index for Airbnb (measured as the number of Google searches for "airbnb"). In particular, tourism can proxy for the heterogeneous tourism popularity across cities. Airbnb history can proxy for unobserved factors that relate to the length of Airbnb's presence in a city. Google search index for Airbnb can proxy for unobserved demand shocks that are common across cities due to Airbnb growth. The hedonic model of the occupancy rate uses the same specification except it also includes the Airbnb price as an additional regressor because the occupancy rate depends on the price. We exclude outliers with Airbnb price below the 5th percentile and above the 95th percentile when running the regressions.

We summarize the covariates that enter each hedonic regression in Columns 5-8 of Table 3a.

The rental and Airbnb supply of comparable units $\left\{S^R_{imT}, S^A_{imt}\right\}$ and the rental and Airbnb price $\left\{p^R_{iT}, p^A_{it}\right\}$ in the hedonic regressions are potentially endogenous variables. We address the endogeneity issue using instruments and discuss the details in Section 5.2. We jointly estimate Equations 9 and 10 as a system of equations and Equations 11 and 12 as another system of equations using three-stage least squares (3SLS) to allow for the correlation of the error terms within each equation system. The regression results are provided in the online appendix. The coefficients have the expected signs.[27]

To generate the expected rent, rental occupancy rate, Airbnb price, and Airbnb occupancy rate for all properties, we first estimate the two systems of equations using the observed revenues and property attributes. Specifically, we use the observed long-term rental data from the AHS to estimate the hedonic models of rent and rental occupancy, and we use the observed Airbnb data to estimate the hedonic models of Airbnb price and occupancy. Once we obtain the estimates, we can generate the expected rent, rental occupancy rate, Airbnb price, and Airbnb occupancy rate for all properties in the Airbnb and AHS data.[28] These expected revenues are used in the property owners' decisions in Equations 1, 4 and 5.

[27] For example, both rent and Airbnb price increase with the number of bedrooms and bathrooms. An increase in the aggregate rental supply is associated with a reduction in rent and rental occupancy. A higher rent decreases rental occupancy. Similarly, a higher aggregate Airbnb supply decreases Airbnb price and occupancy. A higher Airbnb price decreases Airbnb occupancy.

[28] One caveat is that the hedonic models for the Airbnb price and occupancy rate contain the variable for listing type (entire place, private room, shared room), which is not available for properties in the AHS data. We assume that they will be listed on Airbnb as the entire place rather than as private or shared rooms, as most of these properties are the fully available type, meaning that the hosts do not live with the guests. In addition, entire places are the most common type on Airbnb. The results are robust if we allow the properties to be listed as private or shared rooms with a probability equal to the empirical fraction of private or shared room listings in the data.

5 Estimation Method

5.1 Estimation

We use the maximum likelihood estimation (MLE) method to estimate the model. The likelihood function for host i is the joint probability of the first-stage decision on the use of the property and, if the Airbnb option is chosen, the second-stage decision on the number of days to list on Airbnb. The choice set of the first-stage decision depends on the hosts' availability types. There are three sets of hosts in the data:

(1) Hosts that are known to be the fully available type ($\tau_i = 1$). They choose among Airbnb, long-term rental, and the outside option. Let Ω_1 denote this set of hosts. It contains hosts of long-term rental properties, properties that are vacant for the full year, and Airbnb properties that are known to be the fully available type.

(2) Hosts that are known to be the partial available type ($\tau_i = 2$). They choose between Airbnb and the outside option. Let Ω_2 denote this set of hosts. It contains hosts of properties that are vacant for part of the year and Airbnb properties are are known to be the partial available type.

(3) Hosts that we do not observe the types. They can be the fully available type with probability $\Pr(\tau_i = 1 \mid \mathcal{X}_i)$ and the partially available type with probability $\Pr(\tau_i = 2 \mid \mathcal{X}_i)$. Let Ω_U denote this set of hosts. It contains hosts of Airbnb properties that are of unknown types.

For a host in Set Ω_1, his first-stage decision has three options. His contribution to the likelihood function is:

$$\begin{aligned} l_{1i}(\Theta | d_{iT}, s_{it}, \mathcal{X}_i) = \prod_T \{ & \Pr(d_{iT} = R \mid \tau_i = 1, \mathcal{X}_i)^{1(d_{iT}=R)} \cdot \Pr(d_{iT} = O \mid \tau_i = 1, \mathcal{X}_i)^{1(d_{iT}=O)} \\ & \cdot \left[\Pr(d_{iT} = A \mid \tau_i = 1, \mathcal{X}_i) \prod_{t \in T} (\Pr(s_{it} \mid \mathcal{X}_i)) \right]^{1(d_{iT}=A)} \} \end{aligned} \tag{13}$$

where $\mathcal{X}_i$ contains all host demographics, metro area and property characteristics that affect the costs and revenues of host i, $\Pr(d_{iT} \mid \tau_i, \mathcal{X}_i)$ are the probabilities of the first-stage decision, and $\Pr(s_{it} \mid \mathcal{X}_i)$ is the probability of the second-stage decision. For a host in Set Ω_2, his first-stage decision has two options. His contribution to the likelihood function is:

$$\begin{aligned} l_{2i}(\Theta | d_{iT}, s_{it}, \mathcal{X}_i) = \prod_T \{ & \Pr(d_{iT} = O \mid \tau_i = 2, \mathcal{X}_i)^{1(d_{iT}=O)} \\ & \cdot \left[\Pr(d_{iT} = A \mid \tau_i = 2, \mathcal{X}_i) \prod_{t \in T} (\Pr(s_{it} \mid \mathcal{X}_i)) \right]^{1(d_{iT}=A)} \} \end{aligned} \tag{14}$$

For a host in Set Ω_U, his contribution to the likelihood function is:

$$l_{Ui}\left(\Theta|d_{iT}, s_{it}, \mathcal{X}_i\right) = \prod_T \left\{ \left[\sum_{\tau_i=1,2} \Pr\left(\tau_i \,|\, \mathcal{X}_i\right) \cdot \Pr\left(d_{iT} = A \,|\, \tau_i, \mathcal{X}_i\right) \right] \cdot \prod_{t \in T} \left(\Pr\left(s_{it} \,|\, \mathcal{X}_i\right)\right) \right\}^{1(d_{iT}=A)} \tag{15}$$

where $\Pr\left(\tau_i \,|\, \mathcal{X}_i\right)$ is the probability of owner availability types. The full likelihood function combines the probabilities from the three sets of hosts:[29]

$$\mathcal{L}\left(\Theta|d, s, \mathcal{X}, \tau\right) = \prod_i \left[l_{1i}\left(\Theta|d_{iT}, s_{it}, \mathcal{X}_i\right)^{1\{i \in \Omega_1\}} l_{2i}\left(\Theta|d_{iT}, s_{it}, \mathcal{X}_i\right)^{1\{i \in \Omega_2\}} l_{Ui}\left(\Theta|d_{iT}, s_{it}, \mathcal{X}_i\right)^{1\{i \in \Omega_U\}} \right] \tag{16}$$

One caveat is that, as discussed in Section 3.1, we do not observe host demographics for Airbnb properties. For Airbnb properties, the likelihood function is integrated over the zip-code-level demographics distribution $f(\mathcal{X}_i)$ from the ACS data. Given that we conduct a two-step estimation (i.e., estimate the hedonic regressions in the first step and the hosts' decisions in the second step), we correct the standard errors following Murphy and Topel (1985).

5.2 Identification

General identification strategies. We observe three types of information in the data: the revenues, the hosts' first-stage decision, and the hosts' second-stage decision. They are used to identify the revenue-side parameters in the hedonic regressions and the cost-side parameters in the hosts' decisions. The revenue-side parameters are directly identified and obtained by regressing the observed revenues on the observed characteristics. Given the revenues, the cost-side parameters are identified by the hosts' decisions.

The cost-side parameters in the second-stage decision include the Airbnb variable cost parameters $\{\bar{c}^{Av}, \beta^{Av}, \xi_t, \xi_0^{Av}, \xi_1^{Av}, \sigma_2\}$, which are identified by the Airbnb listing pattern. In particular, the average number of days listed and its variation across host demographics, properties, and metro areas identify the Airbnb variable cost parameters $\left\{\bar{c}^{Av}, \beta^{Av}\right\}$. The time-related parameters $\left\{\xi_t, \xi_0^{Av}, \xi_1^{Av}\right\}$ are identified by the listing pattern differences over time and across markets with different lengths of Airbnb history.

The cost-side parameters in the first-stage decision include owner availability type parameters β^a, Airbnb fixed cost parameters $\{\bar{c}_\tau^{Af}, \beta^{Af}, \xi_0^{Af}, \xi_1^{Af}\}$, and the standard deviation of the idiosyncratic shocks σ_1. The fraction of properties that choose Airbnb and its variation across metro areas, demographics, properties, and over time identify the Airbnb fixed cost parameters $\{\bar{c}_\tau^{Af}, \beta^{Af}, \xi_0^{Af}, \xi_1^{Af}\}$. The owner availability type

[29] As discussed in Section 4.3, we observe the owner availability types for two categories of Airbnb properties: 1) properties that are listed every month in the data must be the fully available type ($\tau_i = 1$); 2) properties that are listed as a "private room" must be the partially available type because the hosts live with the guests ($\tau_i = 2$). For these Airbnb properties with observed τ_i, their likelihood function has an additional component, $\Pr\left(\tau_i = \tau \,|\, \mathcal{X}_i\right)^{1(\tau_i=\tau)}$.

parameters β^a are identified from the two groups of Airbnb properties with observed owner availability types (i.e., listed every month in a year; private room listings) through variations in their host demographics, metro areas, and property characteristics.

Note that the cost-side parameters entering the second-stage decision can also be identified by the data on the first-stage decision, and vice versa, as the first and second stages are linked. The expected Airbnb profit from the second stage enters the first-stage decision; thus, the data on the first-stage decision impose over-identifying restrictions on the parameters in the second stage. Similarly, the identification of the parameters in the first stage is also affected by the data on the second-stage decision.

The identification of switching from long-term rental to Airbnb mainly relies on properties with similar observable characteristics. Specifically, the revenue-side prices and occupancy rates and the cost-side fixed and variable costs of hosting in our model are functions of property, host, and metro area characteristics. Therefore, properties with similar characteristics have similar revenues and costs and make similar decisions in a particular setting. As the setting exogenously changes over time, similar properties make different decisions over time in the data, which identifies switching in the model estimation.

More generally, there are exogenous factors in the data that vary over time and across markets that help identify switches from long-term rental to Airbnb. First, on the revenue side, the overall demand for Airbnb grows over time as Airbnb penetrates the market. Cities in which Airbnb entered earlier experienced larger growth. Cities also have different levels of tourism popularity before Airbnb is introduced. Hosts in cities with high tourism popularity are more likely to earn higher revenues on Airbnb when Airbnb is introduced and switch away from long-term rentals. Second, on the cost side, markets differ in conditions that affect Airbnb hosts. For example, cities have different mortgage pressures, which affect hosts' motivations to list on Airbnb. Cities also differ in resources in the accommodations industry before Airbnb is introduced and differ in levels of support in policies on Airbnb after Airbnb is introduced, both of which affect the costs of hosting. Hosts in cities with more favorable conditions are more likely to switch away from long-term rentals. Finally, there is seasonality in both demand-side tourism patterns and supply-side hosting costs. These seasonal fluctuations also affect short-term hosting decisions.

Endogeneity in hedonic regressions. We use instruments to address the endogeneity issue of the rental and Airbnb supply of comparable units $\left\{S^R_{imT}, S^A_{imt}\right\}$ and the rental and Airbnb prices $\left\{p^R_{iT}, p^A_{it}\right\}$.

First, we instrument the rental supply S^R_{imT} using the rental supply of comparable rental units in other markets in year T. The supply of comparable units in other markets is a valid instrument because (1) it is correlated with the supply of comparable units; hosts of these units have similar characteristics and are affected by similar cost shifters as comparable units in the focal market; (2) it is not correlated with the prices of the focal unit because comparable units in other markets do not directly compete with the focal unit and do not affect the focal unit's prices.

Second, we instrument Airbnb supply S^A_{imt} using the 12-month lagged Airbnb supply of comparable units in the focal market. It is a valid instrument because (1) the 12-month lagged units and the current-period comparable units share similar cost shifters that are related to the time of the year, so the 12-month lagged supply and the current-period supply are correlated; (2) the 12-month lagged unobservables and the current-period unobservables are unlikely to be serially correlated given the relatively long time gap, so the 12-month lagged Airbnb supply is uncorrelated with the current-period demand shocks and is uncorrelated with the focal unit's prices. In addition to these instruments, we further include metro-area-level Airbnb regulation score, rent-to-own ratio, and unemployment rate as instruments for Airbnb supply. These variables are valid instruments because they serve as cost shifters and affect the hosts' incentive to list their properties, so they are correlated with Airbnb supply; they do not affect tourists' incentives, so they do not directly affect Airbnb demand.

Third, we instrument the rent p^R_{iT} using average property characteristics of comparable rental properties in other markets in year T. Similarly, we instrument the Airbnb price p^A_{it} using the average property characteristics of comparable Airbnb properties in other markets in month t. The average property characteristics of comparable properties in other markets are valid instruments because (1) characteristics affect hosting costs and in turn prices; comparable properties in other markets have similar characteristics and thus comparable hosting costs as the focal property, so characteristics of comparable units in other markets are correlated with the prices of the focal unit; (2) comparable units in other markets do not directly compete with the focal unit and do not affect the focal unit's occupancy rate, so characteristics of comparable units in other markets do not correlate with the focal unit's occupancy rate.

The instruments pass the weak IV tests.[30]

Exclusion restrictions. Property characteristics, host demographics, and metro area characteristics enter both the cost-side components and the revenue-side regressions. Exclusion restrictions come from the non-overlapping variables. As summarized in Table 3a, each cost component or revenue regression has exclusive variables that do not enter other components. For example, the aggregate supply of Airbnb and rental units affects the revenues but not the costs: they affect the prices and occupancy rates through competition in the market; however, they do not directly influence the hosting costs of an individual host. In addition, tourism (number of air passengers to a city) affects only the revenue side because it captures the demand of tourists, whereas mortgage affects only the cost side because it influences the hosts' incentives. Finally, Airbnb-related variables (e.g., Airbnb history) affect only Airbnb and not the long-term rental

[30]The first-stage regression F-statistics are 864,055 for Airbnb supply, 22,573 for Airbnb price, 119,837 for rental supply and 196 for rent. The incremental R-squared of the first-stage regression when instruments are added is 0.092 for the rental regressions and 0.275 for the Airbnb regressions.

Table 4: Model Fit: First-Stage Decision

[%]	Airbnb	Rental	Vacant full year	Vacant partial year
Observed	1.98	88.70	6.77	2.55
Predicted	2.27	89.74	5.63	2.37

market. In general, the exclusion restrictions stem from the facts that renters (demand) and hosts (supply) face different trade-offs when making their decisions and that Airbnb and the long-term rental market serve different consumers (tourists and local renters).

For the overlapping variables that appear in both the cost and the revenue sides, they are separately identified because we observe three types of information (revenues, first-stage decision of whether to list, and second-stage decision of how long to list) and how they vary by the overlapping variables.[31] Consider the number of bedrooms as an example. It enters both the cost-side components and the revenue-side regressions. First, the revenue-side parameters on the number of bedrooms are directly identified by how the observed prices and occupancy rates change with the number of bedrooms. Second, conditional on the revenues, the cost-side parameters are identified by the variation in the observed first- and second-stage decisions with respect to the number of bedrooms. Specifically, the parameters in the Airbnb fixed cost and variable cost are separately identified if, for example, owners of properties with more bedrooms are more likely to choose Airbnb in the first stage but list shorter in the second stage; in this case, the coefficient on the number of bedrooms is negative in Airbnb fixed cost and positive in Airbnb variable cost.

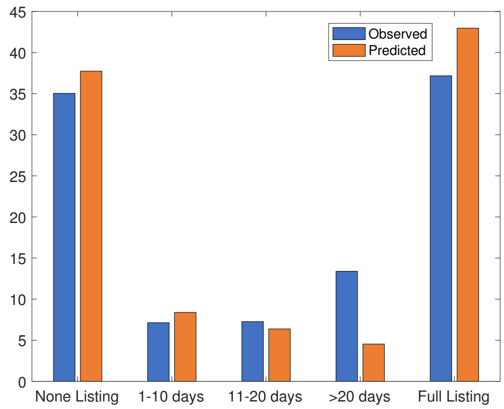
6 Estimation Results

6.1 Model Fit

Table 4 shows the observed and predicted percentages of Airbnb, long-term rental, and outside option properties. Figure 6 shows the observed and predicted Airbnb listing patterns. The model fits the first- and second-stage decisions well. It is also capable of fitting the heterogeneity for both decisions. Figure 7 presents the percentage of Airbnb properties for the first-stage model fit (left) and the percentage of unit-month observations with no listing for the second-stage model fit (right), by property characteristics, metro area, and demographics. The model captures the data patterns across heterogeneous groups. Overall, these results suggest that the model can recover the heterogeneous hosting costs across property characteristics, metro areas, and demographics.

[31]Note that there is no overlap between the covariates in owner availability type (γ_{iT}) and Airbnb fixed cost (c_{iT}^{Af}). This is because owner availability type τ also determines the baseline Airbnb fixed cost $\bar{c}_{\tau}^{Af}$. Therefore, the covariates in owner availability type affect Airbnb fixed cost c_{iT}^{Af} through $\bar{c}_{\tau}^{Af}$ and do not need to be duplicated in c_{iT}^{Af}.

Figure 6: Model Fit: Second-Stage Decision



6.2 Parameter Estimates

Tables 5a and 5b report the parameter estimates for the first-stage and second-stage decisions.

Airbnb variable cost. We use the estimates of $\{\bar{c}^{Av}, \beta^{Av}\}$ and Equation 3 to calculate the predicted variable costs of Airbnb hosting for each property in the data. The values of the predicted costs can be interpreted relative to the hosts' decisions. A smaller predicted variable cost c_{it}^{Av} means that the property is more likely to be listed longer in a month on Airbnb. Across properties in the data, the median predicted variable cost of Airbnb hosting is \$27.9 per day, with a 25 percentile of \$12.1 and a 75 percentile of \$45.2. The estimates suggest that additional bedrooms and facilities increase the variable cost of hosting. The daily cost for an entire place listing is \$29.5 greater than that of a private or shared room listing.

Note that these estimates are very comparable to the prices charged by third-party short-term rental cleaning services, which serve as an out-of-sample validation for our estimates. For example, Tidy charges between \$40 and \$45 for cleaning a one-bedroom unit, which is comparable to our estimate of \$33.5.[32]

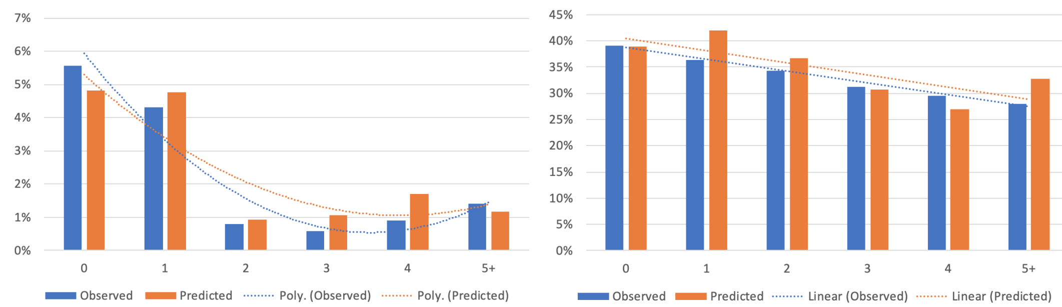
Host demographics and metro area characteristics also affect the Airbnb variable cost and how long hosts list their properties. Hosts have a lower estimated variable cost and list longer if they are younger, have a high school education level and medium income, are female, and are never married. Hosts list longer in cities with a smaller population, a lower density, lower mortgage pressure, more favorable Airbnb regulation scores, and a longer Airbnb history. Hosts also list longer if there are more employment and lower wages in the accommodation industry, as resources in this industry such as room cleaning can also be used for Airbnb hosting and may facilitate Airbnb hosting. The estimated variable cost is lower in 2017 than in 2015 and in winter than in fall.

Owner availability type. The probability of being fully available or partially available varies by host

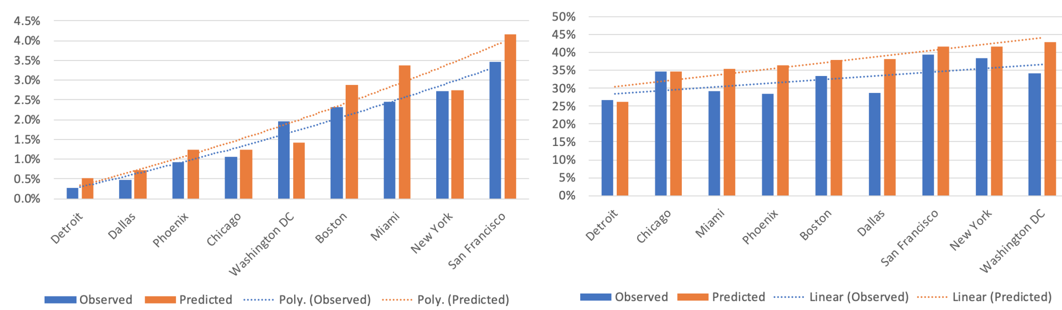
[32] See https://www.tidy.com/compare-house-cleaning-prices

Figure 7: Model Fit by Property Characteristics, Metro Area, and Demographics

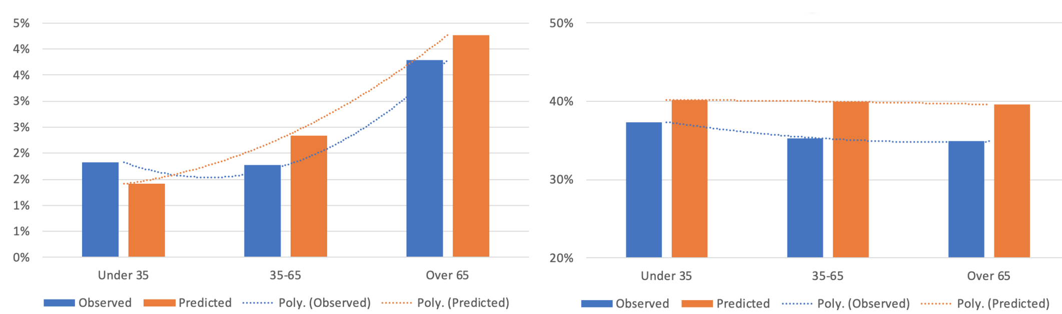
(a) By Property Characteristics (Number of Bedrooms)



(b) By Metro Area



(c) By Demographics (Age)



Note: The y-axis of the plots in the left column represents the percentage of Airbnb properties for the first-stage decision. The y-axis of the plots in the right column represents the percentage of unit-month observations with no listing for the second-stage decision.

Table 5: Parameter Estimates

(a) First-Stage Decision

		Est.	Std.			Est.	Std.
$\bar{c}_1^{Af}$		61.31**	0.984	β^a	age: 35-65	0.0685**	0.0035
$\bar{c}_2^{Af}$		21.49**	1.001		age: over 65	0.6783**	0.0805
σ_1		7.273**	0.0184		edu: high school	1.278**	0.0351
β^{Af}	# of bedrooms	5.571**	0.0984		edu: bachelor	3.689**	0.0255
	# of bathrooms	6.319**	0.0983		income: 50K-100K	-2.986**	0.0751
	# of amenities	-1.420**	0.0085		income: over 100K	-3.033**	0.0830
	type: house (dummy)	4.605**	0.0522		gender: male	2.231**	0.0051
	studio (dummy)	0.588**	0.191		marital status: never	-0.390**	0.0563
	mortgage	-9.059**	0.3257		population	0.231**	0.0039
	employment in accomm.	-1.173e-4	1.489e-4		density	-0.713**	0.0328
	wage in accomm.	6.953e-4**	2.720e-4		single bedroom (dummy)	-3.086**	0.0201
	year fixed effect	-0.648**	0.0701		constant	-3.887**	0.0240
	Airbnb history	1.389**	0.0381				

(b) Second-Stage Decision

		Est.	Std.		Est.	Std.
$\bar{c}^{Av}$		59.41**	1.275	σ_2	51.55**	0.140
β^{Av}	age: 35-65	8.195**	0.145	population	0.778**	0.067
	age: over 65	9.619**	0.310	density	3.516**	0.424
	edu: high school	-217.0**	0.700	mortgage	37.05**	0.121
	edu: bachelor	-127.8**	0.666	employment in accomm.	-2.889**	0.140
	income: 50K-100K	-10.063**	0.691	wage in accomm.	1.135e-4	7.921e-4
	income: over 100K	5.087**	0.157	Airbnb regulation score	-23.79**	0.109
	gender: male	4.228**	0.391	year fixed effect	-8.574**	0.215
	marital status: never	-4.447**	0.0458	Airbnb history	-11.52**	0.083
	# of bedrooms	5.197**	0.146	summer	12.26**	0.320
	# of bathrooms	-0.738**	0.039	fall	21.00**	0.046
	# of amenities	1.258**	0.062	winter	-4.454**	0.162
	entire room (dummy)	29.53**	0.224			

Note: * and ** represent significance at the 5% and 1% levels. The following variables are in logged form: population, density, mortgage, Airbnb history. Employment in the accommodation industry is in percentages, and wages in the accommodation industry are in $10k. The host demographics are captured by dummy variables, one for each demographic group. The baseline demographics group is age under 35, education below high school, income below 50k, female, and married. For Airbnb properties, we do not observe individual host demographics and impute them using the local zip-code-level demographics. The demographic dummy variables take the value of the percentage of a specific demographic group in the zip code.

demographics and metro area. The estimates of β^a suggest that hosts are more likely to be the fully available type if they are seniors, have a bachelor degree, have a low income, are male, married and live in cities with a larger population and a lower density. Hosts are more likely to be the partially available type if they own a single-bedroom property. Note that the owner availability type also affects the baseline Airbnb fixed cost $\bar{c}_{\tau}^{Af}$, which further determines whether the host chooses Airbnb.

Airbnb fixed cost. We use the estimates of $\left\{\bar{c}_{\tau}^{Af}, \beta^{Af}\right\}$ and Equation 7 to calculate the predicted fixed costs of Airbnb hosting for individual properties in the data. The values of the predicted costs can be interpreted relative to the hosts' decisions. A smaller predicted fixed cost c_{iT}^{Af} means that the property is more likely to be listed on Airbnb. We find that the median predicted Airbnb fixed cost of Airbnb properties is \$633 per month (\$21.1 per day), with a 25th percentile of \$338 per month (\$11.3 per day) and a 75th percentile of \$2368 per month (\$78.9 per day). Note that the average daily price is \$148.7 according to Table 1. The fixed cost can include the psychological cost of embracing the new platform technology and renting out property to transient guests, as well as other tangible costs, such as learning how to set up the technology and earn higher profits on Airbnb (e.g., set prices) and preparing property photos, descriptions, furnishings, and amenities. The fixed cost can be quite large when, for example, property owners are reluctant to learn the new technology and find it uncomfortable to rent their home to complete strangers or when they must procure more furnishings and amenities to set up their properties as Airbnb listings. In fact, the psychological cost for the hosts is one of the major obstacles that Airbnb needs to overcome to "convince people to open up their home and allow guests to stay," especially after cases of hosts reporting that their properties were trashed after hosting guests or that they faced safety issues.[33] The learning cost of hosting is another major factor for which Airbnb needs to compensate the hosts, as evident by Airbnb's significant spending on technology and administrative costs associated with the hosts.[34]

We find that the Airbnb fixed cost is higher for properties with more bedrooms and bathrooms and higher for a house than an apartment. The fixed cost is lower and property owners are more likely to choose Airbnb in cities with higher employment and a lower wage in the accommodation industry, and with a longer Airbnb presence. Property owners are also more likely to choose Airbnb in cities where mortgages are high, which might be because property owners leverage Airbnb as an additional income source to pay their mortgages.[35] In fact, the primary use of the hosting income is to pay mortgages according to a survey

[33]See https://www.growthmanifesto.com/airbnb-growth-strategy and https://www.vox.com/2020/2/12/21134477/airbnb-loss-profit-ipo-safety-tech-marketing.

[34]See https://www.vox.com/2020/2/12/21134477/airbnb-loss-profit-ipo-safety-tech-marketing.

[35]The estimates suggest that mortgage pressure reduces the Airbnb fixed cost but increases the Airbnb variable cost. This means that hosts in cities with a high mortgage pressure are more likely to choose Airbnb in the first stage but to list for less time in the second stage. This may be because hosts in these cities are more likely to use Airbnb to pay their mortgage while they are still living in the properties; although they are willing to list, their cost of managing the listing is high.

conducted by Airbnb.[36] Airbnb hosts can even use Airbnb income as proof of worth when applying for mortgage refinancing.[37] Finally, the fully available type of hosts have higher Airbnb fixed costs and are less likely to choose Airbnb than the partially available type of hosts. This may be because these fully available type of hosts have long-term rental as their default option and are reluctant to overcome the inertia and adopt the new technology of Airbnb.

7 Counterfactuals

Given the model estimates, we conduct a series of counterfactual analyses.[38] The first set of analyses evaluate the impact of Airbnb on rental market and housing affordability. We simulate the property owners' choices when Airbnb is present versus when it is not present. We compare the two sets of equilibrium outcomes to evaluate how many Airbnb properties would have been listed on the long-term rental market without Airbnb (i.e., cannibalization effect of Airbnb) and how many properties would not (i.e., market expansion effect of Airbnb). The second set of counterfactual analyses evaluate the impact of a series of policies intended to ensure the supply and affordability of rental housing. We consider the two prevailing short-term rental regulations on Airbnb in practice, imposing taxes and limiting the maximum number of days that a property can be listed. We further propose a new policy and assess the desirability of different policies. Finally, we investigate rent control policy on long-term rental, particularly how its impact can be affected by the presence of Airbnb. In all counterfactual analyses, we assume that the set of properties is exogenously given in the data and abstract away from the case in which hosts purchase or build new properties because of the introduction of Airbnb.

7.1 Equilibrium

When solving for new equilibrium under counterfactual scenarios, we allow the rent, rental occupancy rate, Airbnb price and occupancy rate to endogenously change according to the hedonic regressions in Section 4.4. Specifically, given different counterfactual scenarios, the number of properties and the types of properties that choose long-term rental and Airbnb can change. The new characteristics and the new aggregate Airbnb and rental supply enter the hedonic models and generate a new set of expectations on rent, rental occupancy

[36] See https://www.airbnbcitizen.com/the-airbnb-community-in-seattle/

[37] See https://www.cnbc.com/2018/02/22/homeowners-are-using-airbnb-rental-income-to-refinance-mortgages.html

[38] In practice, Airbnb can affect rental housing affordability by changing rental supply (i.e., the number of switchers) and rent, both of which are allowed to endogenously change in our counterfactual analysis. We focus on presenting the changes in rental supply in this section because the changes in rent are found to be very small (less than 1%). This is because the number of Airbnb properties, compared to long-term rental and vacant properties, is still very small in both the data and the counterfactual analysis. Given the current market landscape, Airbnb's impact on long-term rentals is limited; Airbnb mainly affects the long-term rental market by reducing rental supply rather than raising rental prices. The impact on rent could become significant if Airbnb accounts for a larger market share in the future.

rate, Airbnb price and occupancy rate. The equilibrium is defined as a fixed point of the Airbnb price, Airbnb occupancy rate, aggregate Airbnb supply, rent, rental occupancy rate, and aggregate rental supply $\{p_{it}^A, \phi_{it}^A, S_{imt}^A, p_{iT}^R, \phi_{iT}^R, S_{imT}^R\}$. The numerical algorithm to solve for the equilibrium is as follows:

1. Let superscript (k) denote the k-th iteration. Begin with the aggregate Airbnb supply $S_{imt}^{A(k)}$ and aggregate rental supply $S_{imT}^{R(k)}$. Given $S_{imt}^{A(k)}$ and $S_{imT}^{R(k)}$, construct the expected rent $p_{iT}^{R(k+1)}$, rental occupancy rate $\phi_{iT}^{R(k+1)}$, Airbnb price $p_{it}^{A(k+1)}$, and Airbnb occupancy rate $\phi_{it}^{A(k+1)}$ for each property using the hedonic regressions in Equations 9, 10, 11, and 12.

2. Given the updated $p_{it}^{A(k+1)}$, $\phi_{it}^{A(k+1)}$, $p_{iT}^{R(k+1)}$, and $\phi_{iT}^{R(k+1)}$, solve the property owners' problem under each counterfactual policy. Compute the updated aggregate Airbnb supply $S_{imt}^{A(k+1)}$ and aggregate rental supply $S_{imT}^{R(k+1)}$.

3. Check for the convergence of $\left|p_{it}^{A(k+1)} - p_{it}^{A(k)}\right|$, $\left|\phi_{it}^{A(k+1)} - \phi_{it}^{A(k)}\right|$, $\left|S_{imt}^{A(k+1)} - S_{imt}^{A(k)}\right|$, $\left|p_{iT}^{R(k+1)} - p_{iT}^{R(k)}\right|$, $\left|\phi_{iT}^{R(k+1)} - \phi_{iT}^{R(k)}\right|$, and $\left|S_{imT}^{R(k+1)} - S_{imT}^{R(k)}\right|$. If convergence is not achieved, return to Step 1.

We initialize the algorithm using the observed aggregate Airbnb supply and aggregate rental supply. Varying the initialization point produces robust results.

Note that we use the hedonic regression coefficients estimated from the observed data in the counterfactual analyses. These coefficients capture how hosts form expectations about prices and occupancy rates in the data. The underlying assumption is that hosts in the counterfactuals form expectations in the same way as they do in the observed scenario. We believe that it can be a reasonable assumption in the short run in our setting.[39] This assumption is also similar to the assumptions made in the existing literature on durable product demand (e.g., Nair 2007, Gowrisankaran and Rysman 2011).[40] A limitation of the hedonic regression approach is that it captures how prices and occupancy rates are determined in a simplified and non-structural way. The regression coefficients are estimated using data in the current stage of the market where Airbnb is relatively small. The results may not apply to the long term if Airbnb's presence becomes significant relative to long-term rental market or if the ways that prices and occupancy rates are determined systematically change in the long run.

[39]First, the coefficients in Equations 9-10 capture how rent and rental occupancy are determined in the long-term rental market. Given that the size of Airbnb is relatively small (2.5% of the long-term rental market), Airbnb's presence and the policies on Airbnb are unlikely to systematically change the way rent and rental occupancy are determined in the long-term rental market in the short run. Second, the coefficients in Equations 11-12 capture how price and occupancy are determined on Airbnb. In practice, Airbnb hosts set prices by accounting for property characteristics, location, and seasonal demand; some hosts use third-party pricing services, which account for similar pricing factors (Li and Srinivasan 2019). These factors are captured in Equations 11-12. The ways these factors affect Airbnb prices and occupancy rates may not systematically change in the short run when certain regulations are introduced.

[40]Specifically, literature on durable product demand assumes that consumers expect that the prices follow an AR (1) process. First, the coefficients of the AR (1) process are estimated using the observed prices. Second, fixing these coefficient estimates, consumers make new product adoption decisions in the counterfactual analyses. As another example, Li and Srinivasan (2019) first use the observed price and supply to estimate how Airbnb price and supply are determined by observed characteristics and supply. Then, they use the estimated coefficients to obtain new price and supply in the equilibrium in the counterfactual analysis.

7.2 Cannibalization and Market Expansion

We first evaluate the impact of Airbnb on the long-term rental market and housing affordability. Airbnb can create both a negative impact of cannibalization and a positive impact of market expansion in the rental housing market. To evaluate the impact of Airbnb, we use the model estimates to simulate the property owners' choices when Airbnb is present versus when it is not present. We allow prices and occupancy rates to endogenously change when solving for new equilibrium outcomes under both scenarios.

Intuitively, hosts' decisions can be different with and without Airbnb. Some hosts choose the outside option when Airbnb is not present and choose Airbnb when it becomes available. These hosts represent the market expansion effect of Airbnb: they would not have listed on the long-term rental market and benefit from having Airbnb as an additional income source. Some hosts choose the long-term rental market when Airbnb is not present and choose Airbnb when it becomes available. These hosts are switchers from the long-term rental market and represent the cannibalization effect of Airbnb or the reduction in the long-term rental supply due to Airbnb.

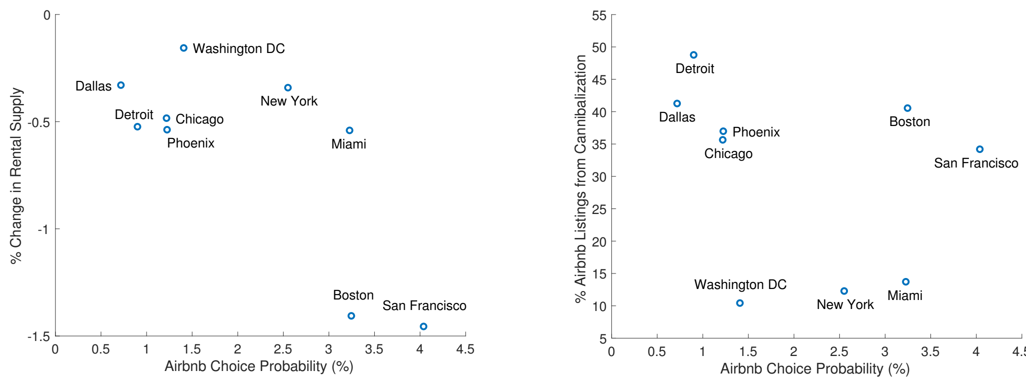
Note that the fully available hosts have the long-term rental option, whereas the partially available hosts do not. Therefore, only the fully available hosts can switch from the long-term rental market; the partially available hosts cannot. In general, the fully available hosts choose among all three options and can thus create both cannibalization and market expansion. The partially available hosts only choose between Airbnb versus vacant and can only create market expansion. Specifically, cannibalization can come from one situation: a fully available host would have listed the property on the long-term rental market and chooses to list on Airbnb when Airbnb is present. Market expansion can come from two situations: (1) a fully available host who has an unoccupied unit would have kept the entire unit vacant without Airbnb and chooses to list on Airbnb when Airbnb is present; (2) a partially available host would not have rented out without Airbnb and chooses to list on Airbnb when Airbnb is present.

Let D^{R0} and D^{R1} denote the equilibrium number of long-term rental units without and with Airbnb. Let D^A denote the equilibrium number of Airbnb units when Airbnb is present. Among Airbnb units, the number of switchers or cannibalization units is $D^{R0} - D^{R1}$ and the number of non-switchers or market expansion units is $D^A - (D^{R0} - D^{R1})$. We use two measures to evaluate Airbnb's impact. The first is the percentage change in rental supply due to Airbnb ($\frac{D^{R1}-D^{R0}}{D^{R0}}$), which captures the negative impact of Airbnb on the long-term rental market. The second is the percentage of Airbnb units that come from cannibalization, or the cannibalization rate, $\frac{D^{R0}-D^{R1}}{D^A}$. This represents the percentage of switchers among all Airbnb units (switchers and non-switchers), which captures the relative sizes of the negative and positive impacts of Airbnb. The measures are linked to the cost estimates of our model, as hosts with a high (low) Airbnb hosting cost are

Figure 8: Cannibalization and Market Expansion by Metro Area

(a) Change in Rental Supply

(b) Cannibalization Rate



more likely to remain in (leave) the long-term rental market when Airbnb is introduced.

We first plot the percentage change in rental supply across metro areas in Figure 8a. We find that Airbnb causes a mild reduction in the rental supply, ranging from -0.16% in Washington D.C. to -1.46% in San Francisco. The reduction in the rental supply tends to be larger in metro areas where Airbnb is a popular choice for property owners.

However, the percentage change in the rental supply alone does not provide a holistic view of Airbnb's impact. We must also consider the market expansion effect created by Airbnb. We plot the cannibalization rate, or the percentage of switchers, across metro areas in Figure 8b. We find that the percentage of switchers varies significantly, ranging from 10.4% in Washington D.C. to 48.8% in Detroit.

Interestingly, although the reduction in the rental supply is greater in metro areas where Airbnb is popular, the cannibalization rate is not necessarily larger in these areas. For example, Miami and New York are among the cities with the highest Airbnb popularity and the largest rental supply reduction; however, their percentages of switchers are among the lowest. This suggests that most of the Airbnb listings in Miami and New York are from market expansion rather than cannibalizing the rental supply. Thus, city regulators must thoroughly evaluate both the positive and negative impacts of Airbnb.

Table 6 presents the two measures (the percentage change in the rental supply $\frac{D^{R1}-D^{R0}}{D^{R0}}$ and the percentage of Airbnb units from cannibalization $\frac{D^{R0}-D^{R1}}{D^{A}}$) by property characteristics and demographics. In terms of property characteristics, the reduction in rental supply is largely concentrated among lower priced, more affordable units rather than among higher priced luxury units. A basic studio or one-bedroom apartment originally on the long-term rental market is more likely to be taken off than a house with multiple bedrooms and more amenities. However, the market expansion effect is also larger for affordable units, leading to a lower cannibalization rate for these units. In terms of demographics, the reduction in rental supply and the

Table 6: Cannibalization and Market Expansion by Property Characteristics and Demographics

(a) Property Characteristics

[%]		$\frac{D^{R1}-D^{R0}}{D^{R0}}$	$\frac{D^{R0}-D^{R1}}{D^{A}}$	[%]		$\frac{D^{R1}-D^{R0}}{D^{R0}}$	$\frac{D^{R0}-D^{R1}}{D^{A}}$
# of Bedrooms	0	-1.47	35.36	# of Amenities	1	-0.82	7.56
	1	-0.70	13.53		2	-0.54	23.66
	2	-0.45	44.73		3	-0.33	21.64
	3	-0.42	39.12		4	-0.56	18.58
	4	-0.38	21.08		5	-0.72	23.55
	5+	-0.04	3.13		6	-0.78	26.10
# of Bathrooms	1	-0.69	22.97	Property Type	Apt	-0.56	22.37
	2	-0.45	16.38		House	-0.49	22.43
	3	-0.23	31.80	Listing Type	Entire Place	-0.54	31.15
	4	-0.15	16.83		Private Room	-0.01	0.01

(b) Demographics

[%]		$\frac{D^{R1}-D^{R0}}{D^{R0}}$	$\frac{D^{R0}-D^{R1}}{D^{A}}$	[%]		$\frac{D^{R1}-D^{R0}}{D^{R0}}$	$\frac{D^{R0}-D^{R1}}{D^{A}}$
Age	under 35	-0.29	19.69	Income	under 50K	-0.33	14.80
	35-65	-0.43	17.06		50K-100K	-0.70	35.87
	over 65	-1.68	38.44		over 100K	-0.94	25.83
Education	under	-0.76	39.15	Gender	male	-0.76	33.39
	high school	-0.45	18.93		female	-0.35	14.12
	bachelor's	-0.12	3.53	Marital Status	never married	-0.68	28.13
					other	-0.46	19.03

cannibalization rate are higher for senior, lower education, medium-income, male, and never married hosts.

Importantly, the results speak to how Airbnb affects housing affordability. We find suggestive evidence that Airbnb does raise affordable housing concerns, as rental supply reduction is larger among affordable units. However, the market expansion effect is also larger for affordable units, as the fraction of non-switchers is larger among affordable units on Airbnb. This suggests that, interestingly, affordable units are major sources of both the negative cannibalization impact and the positive market expansion impact of Airbnb. Although Airbnb harms local renters by reducing the affordable rental supply, it also serves as a valuable income source and benefits local hosts who own affordable units and are more likely to be less economically advantaged. Therefore, policy makers need to strike a balance between local renters' affordable housing concerns and local hosts' income source needs.

Note that an observed "full-time" ("part-time") listing does not necessarily imply cannibalization (market expansion). In other words, it is not appealing to assume, without modeling the hosts' decisions, that all full-time hosts on Airbnb are switchers and should have been listed on the long-term rental market. Therefore, our structural model framework is helpful in recovering the underlying decision-making process of the hosts and identifying the actual potential switchers. Specifically, cannibalization occurs when hosts switch from long-term rentals to Airbnb. Even if hosts list their properties on Airbnb full time, it is not cannibalization if they would not have chosen the long-term rental option in the absence of Airbnb; they could have chosen to keep their properties vacant in the absence of Airbnb if their costs (revenues) of long-term rental are high (low). In contrast, part-time listings can be due to cannibalization if they would have been in the long-term rental market in the absence of Airbnb. This is possible if the Airbnb profit is large enough to allow hosts to list part time and still earn more than listing in the long-term rental market.

7.3 Policy Evaluation

This subsection evaluates the impact of various policies intended to ensure rental housing supply and affordability: regulations on Airbnb (e.g., tax and day limit) and long-term rentals (e.g., rent control).

7.3.1 Policy Implementation

Short-term rental regulations on Airbnb. We focus on three types of regulations on Airbnb. The first and second types are the most prevalent policies in practice. The third is a new policy we propose based on our findings about Airbnb and housing affordability.

Specifically, the first type of regulation limits the maximum number of days that a property can be listed on short-term rental platforms (e.g., a maximum of 90 days in San Francisco and 120 days in Los Angeles). The second type charges a transient occupancy tax as a fixed percentage of the listing price (e.g., 8.5% in Philadelphia and 14% in Los Angeles), which is similar to a hotel occupancy tax. Both the first and second types of regulations are motivated by concerns about switchers from the long-term rental market to Airbnb, which can hurt the rental housing supply and affordability. By 2020, many cities have imposed these types of regulations on Airbnb.[41]

The third type of regulation is a convex tax that charges a higher tax on expensive units and a lower tax on affordable units. We propose this new policy because it shares a similar goal with the existing two policies and can help reduce the proportion of switchers. Heterogeneous properties have different proportions of switchers. To reduce switching, policy makers can consider charging a higher tax rate on properties with a larger proportion of switchers. As shown in Section 7.2, we find that affordable units have a lower proportion of switchers while expensive units have a higher proportion of switchers. Therefore, it can be helpful to charge a higher tax rate on the expensive units among which the proportion of switchers is larger. This constitutes a convex tax for which the tax rate increases as the listing price increases.

We need to operationalize the three types of regulations in the counterfactual analyses. To operationalize the first regulation, day limit, we simulate the case in which hosts are able to list up to a certain number of

[41] See https://www.airbnb.com/help/article/864/los-angeles-ca#nightlimits and https://www.airbnb.com/help/article/2509/in-what-areas-is-occupancy-tax-collection-and-remittance-by-airbnb-available.

months in a year. Specifically, we calculate the optimal number of days to be listed per month in the second stage. We allow the hosts to choose the months that have the highest expected profits up to the pre-specified maximum number of months. Based on the total ex ante expected profit from the chosen months, they choose among Airbnb, long-term rental, and the outside option in the first stage. To operationalize the second regulation, occupancy tax, we use a linear tax as a fixed percentage of the listing price. To account for tax pass-through, let p_{it}^{A} denote the listing price paid by consumers and $p_{it}^{A,host}$ denote the price received by hosts. The price paid by consumers p_{it}^{A} enters the hedonic regressions in Equations 11 and 12, whereas the price received by hosts $p_{it}^{A,host}$ enters the hosts' decisions in Equations 1, 4 and 5. The prices and occupancy rates are determined such that $p_{it}^{A,host} = p_{it}^{A} - t_1 \cdot p_{it}^{A}$ in equilibrium, where t_1 is the tax rate and $0 < t_1 < 1$. To operationalize the third regulation, convex tax, we use $p_{it}^{A,host} = p_{it}^{A} - t_2 \cdot (p_{it}^{A})^2$ such that the implied average tax rate as a fraction of the listing price $t_2 p_{it}^{A}$ increases with the listing price.

Long-term rental regulations: rent control. We focus on one type of regulation on long-term rental, rent control, which is commonly observed in practice and is intended to ensure rental housing affordability. Rent control is a system of laws placing a maximum price, or a "rent ceiling," on what landlords may charge tenants. It covers a spectrum of regulations that can vary from setting the absolute amount of rent that can be charged with no allowed increases to placing different limits on the amount that rent can increase. These restrictions may continue between tenancies or may be applied only within the duration of a tenancy. As of March 2019, the states of California, Maryland, New Jersey, New York, and Oregon, and the city of Washington D.C. have some rent control or stabilization policies on the books, and 37 states prohibit or ban rent control outright.[42]

The rent control policy impacts hosts' incentives to rent and was implemented before Airbnb was introduced. The introduction of Airbnb further impacts hosts' incentives to rent and can interfere with the rent control policy. Economists have concluded that rent control policies are destructive. According to a 1990 poll of 464 economists, 93% of U.S. respondents agreed, either completely or with provisos, that "a ceiling on rents reduces the quantity and quality of housing available" (Alston, Kearl, and Vaughan 1992). We argue that the negative impact of rent control policy can be exacerbated when another profitable option for hosts, Airbnb, is available. We illustrate how the presence of Airbnb affects the impact of rent control policies by simulating policy outcomes with and without Airbnb.

To operationalize the rent control policy, we assume that the rent is capped at $r\%$ below the observed rent where $r\%$ can mimic the type of rent control that limits the maximum percentage of rent increase from the previous year.

[42] See https://www.curbed.com/2019/3/8/18245307/rent-control-oregon-housing-crisis

7.3.2 Short-Term Rental Regulations

Overall policy impact. Figure 9a shows the effect of short-term rental regulations by plotting the number of switchers (cannibalization) on the x-axis and the number of non-switchers (market expansion) on the y-axis. Each line represents one type of regulation, and each point on the line represents a particular level of regulation. For example, the level of regulation for the maximum month limit varies from 12 months to 3 months, and the level of regulation for the linear tax rate varies from 0% to 90%. Arrow (a) indicates the direction of stricter regulation, for example, a higher tax rate and lower number of months allowed to list. Comparing different levels of regulation within each policy, we find that there is a trade-off in terms of choosing the level of regulation: stricter regulations help reduce the number of switchers (cannibalization); however, they also reduce the number of non-switchers (market expansion).

A desirable policy should reduce the negative impact of Airbnb (switcher or cannibalization) while maintaining the positive impact of Airbnb (non-switcher or market expansion). The cannibalization rate is a measure that accounts for both impacts. Therefore, we examine the following measure when comparing policies:

(1) The cannibalization rate, or the fraction of switchers, among all listings (switchers and non-switchers).

We find that our proposed policy of a convex tax is the most desirable among the three short-term rental regulations. As shown in Figure 9b, the convex tax induces a lower cannibalization rate than the other two policies. The linear tax is the second-best policy, and the month limit is the worst.

Differential impact on hosts. In addition to the overall policy impact, we examine how the policies differentially affect heterogeneous host groups. In particular, Airbnb provides hosts an alternative income source, which is especially valuable for less economically advantaged hosts. If the economically advantaged hosts earn more profits, the distribution of income among hosts will be more unequal and social inequality will be exacerbated. In practice, there have been continuing concerns that Airbnb exacerbates income disparity as the gains from Airbnb are disproportionately skewed to those with more wealth.[43] Imposing the regulations can induce a redistributive effect among hosts and affect income and social equality.

In addition to that defined by measure (1), a desirable policy should prevent the distribution of income among hosts from being skewed to those economically advantaged hosts who own expensive units and already have abundant resources. We define two additional measures of policy desirability:

(2) The fraction of total host profits earned by owners of luxury units.

(3) The fraction of total host profits earned by economically advantaged hosts.

[43]For instance, see https://www.usnews.com/news/cities/articles/2019-05-02/airbnbs-controversial-impact-on-cities and https://www.epi.org/publication/the-economic-costs-and-benefits-of-airbnb-no-reason-for-local-policymakers-to-let-airbnb-bypass-tax-or-regulatory-obligations/.

Figure 9: Short-Term Rental Regulations

(a) Number of Switchers and Non-switchers (b) Cannibalization Rate

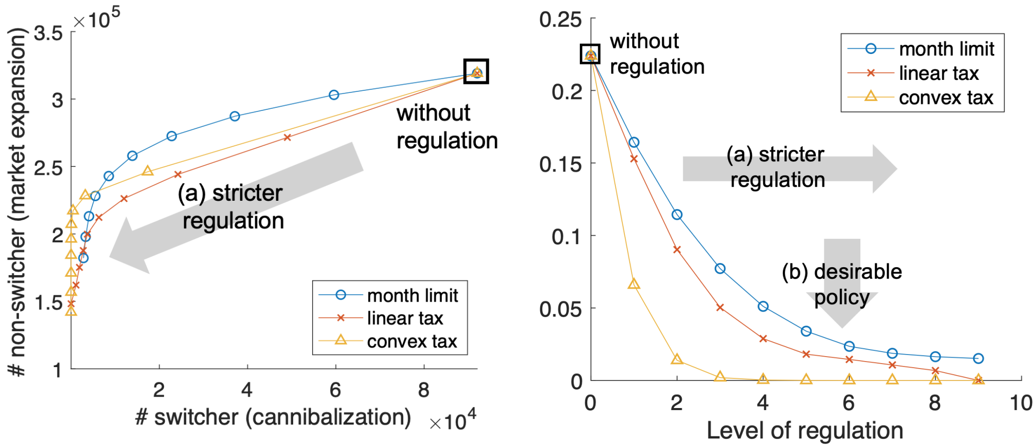
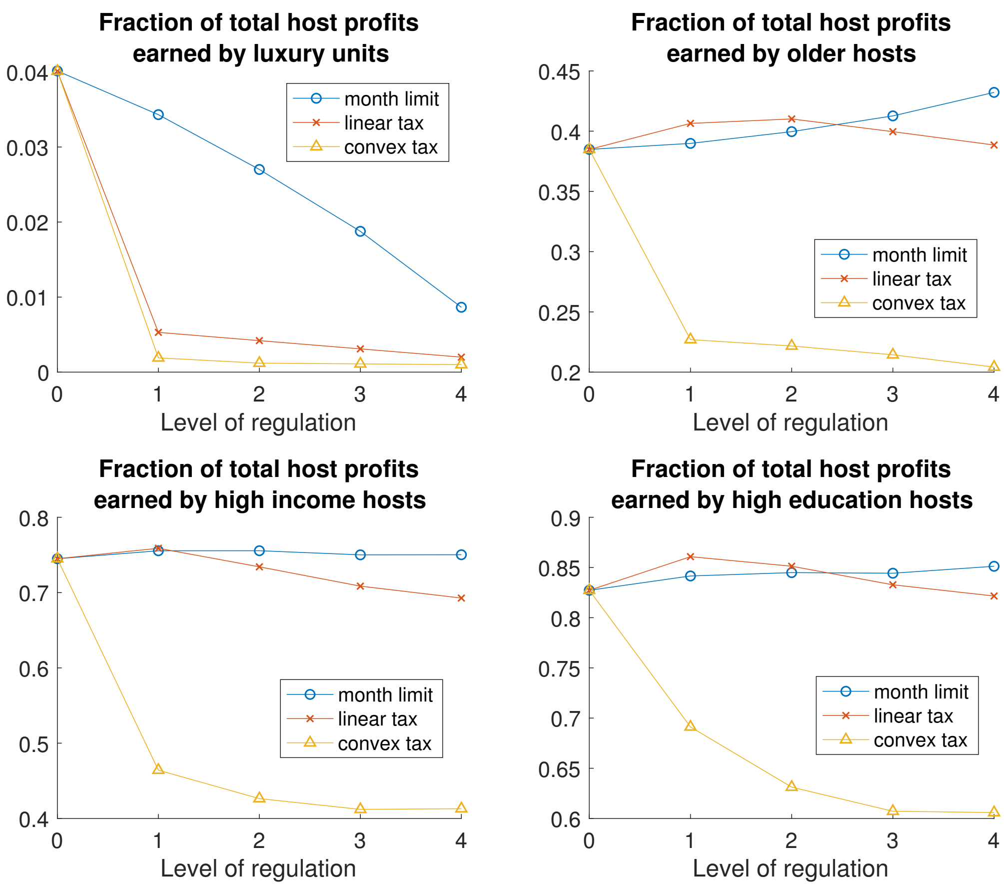


Figure 10: Short-Term Rental Regulations: Differential Impact on Hosts



Specifically, host profit equals (after-tax) revenue subtracts hosting cost. We calculate the host profit earned by each host and examine the fraction of total host profits earned by specific host groups. In Figure 10, we plot the fraction of total host profits earned by owners of luxury units (4 bedrooms or above), high-income hosts (income more than 100k), older hosts (age above 65), and high-education hosts (bachelor's degree or higher). We find that the convex tax again performs best in terms of having the smallest fraction of total host profits earned by owners with luxury units, high income, age, or education.

Overall, our proposed policy of a convex tax outperforms the other two policies in all three measures: (1) reducing the cannibalization rate, (2) reducing the fraction of total host profits earned by owners of luxury units, and (3) reducing the fraction of total host profits earned by economically advantaged hosts. The linear tax appears to perform better than the month limit. The convex tax performs best because the percentage of switchers is larger among higher priced luxury units than among lower priced affordable units. The convex tax discourages taking higher price properties off the long-term rental market, which helps limit cannibalization, but has less influence on lower priced properties, which helps maintain market expansion.

7.3.3 Long-Term Rental Regulations: Rent Control

To examine how Airbnb and rent control policies affect each other, we simulate market outcomes under four scenarios: (a) there is no rent control policy, and Airbnb is not available; (b) rent is controlled, and Airbnb is not available; (c) there is no rent control policy, and Airbnb is available; and (d) rent is controlled, and Airbnb is available. The difference between a (c) and b (d) represents the negative impact of rent control in the absence (presence) of Airbnb. The difference between a (b) and c (d) represents the negative impact of Airbnb in the absence (presence) of rent control. Importantly, we find that Airbnb and rent control can exacerbate each other's negative impact.

First, we find that Airbnb's presence can amplify the negative impact of rent control. In Table 7, the first column shows the percentage decrease in the rental supply due to rent control in the absence of Airbnb, and the second column shows the percentage when Airbnb is present. Consistent with the near-consensus among economists discussed above, we find that rent control policy reduces the rental supply. Importantly, this negative impact of rent control policy is exacerbated when Airbnb is available: the reduction in rental supply due to rent control is larger with Airbnb than that without Airbnb. This exacerbating effect is even more prominent with stricter rent control policies. This is because Airbnb provides property owners with an alternative option in addition to listing on the long-term rental market. When faced with a rent control policy, more property owners quit the long-term rental market and switch to Airbnb.

Second, we find that the presence of rent control can also amplify Airbnb's negative impact. Table 8 shows the percentage decrease in rental supply induced by Airbnb under varying strictness of rent control.

Table 7: Impact of Airbnb on the Negative Effect of Rent Control Policies

	% Change in the Rental Supply Due to Rent Control	
Level of Rent Control (r)	without Airbnb	with Airbnb
5.0%	-0.60	-0.64
10.0%	-1.22	-1.29
15.0%	-1.85	-1.96
20.0%	-2.49	-2.63

Table 8: Impact of Rent Control Policies on the Negative Effect of Airbnb

Level of Rent Control (r)	None	5.0%	10.0%	15.0%	20.0%
% Change in the Rental Supply Due to Airbnb	-0.54	-0.58	-0.61	-0.65	-0.68

The percentage reduction in rental supply due to Airbnb is larger when a rent control policy is in effect and increases as the rent control policy becomes stricter.

Overall, the presence of Airbnb and a rent control policy can each have a negative impact on the long-term rental supply. We find that when both are present, they can exacerbate each other's negative impact. Thus, policy makers must exercise caution when implementing rent control policies in the presence of Airbnb.

8 Conclusion

We investigate how Airbnb affects rental supply and affordability and provide policy implications for short-term rental regulations and long-term rent control. We model property owners' decisions in two stages: (1) the yearly decision of choosing among Airbnb, the long-term rental market, and the outside option and (2) the monthly decision on how many days to list on Airbnb if they choose Airbnb in the first stage. Given the revenue data on rent, rental occupancy rate, Airbnb price, and Airbnb occupancy rate, we estimate the hosting costs of property owners.

We find that Airbnb mildly cannibalizes the rental market but has a market expansion effect. The percentage of switchers varies significantly across cities. The rental supply reduction is larger for lower priced affordable units than for higher priced luxury units, suggesting that Airbnb can raise concerns about housing affordability. However, the market expansion effect is also greater for affordable units, suggesting that owners of affordable units benefit more from having Airbnb as an income source. Metro areas where Airbnb is popular (e.g., San Francisco, New York, and Miami) experience a larger reduction in the long-term rental supply due to Airbnb; however, some of them benefit more from a larger market expansion effect, suggesting that the percentage of switchers is not necessarily greater in those cities.

The counterfactual results suggest that short-term rental regulations help reduce cannibalization; however, they also reduce market expansion. We assess commonly used regulations, such as limiting the number of days that a property can be listed and a linear tax, and propose a new convex tax that charges a higher tax on expensive units. We show that the proposed convex tax outperforms the linear tax, which further outperforms the day limit according to three measures of policy desirability: (1) reducing the cannibalization rate, (2) reducing the fraction of total host profits earned by owners of luxury units, and (3) reducing the fraction of total host profits earned by economically advantaged hosts (e.g., high-income, older, or high-education hosts). Finally, rent control must be implemented with greater caution when Airbnb is available, as lower profits from long-term rentals can lead landlords to switch to Airbnb and exacerbate the side effect of a rent control policy.

This study has a few limitations that represent directions for future research. First, the set of policy desirability measures we examine cannot capture every aspect of the policy effects. We focus on the effects on hosts' decisions given that our data set allows us to model hosting behaviors. However, many other potential effects are important for policy makers but could not be addressed in this paper, for example, the cascading effects of hosts' behaviors, effects on renters, and long-term effects on new home purchases and construction. Exploring these effects offers promising directions for future research.

Second, we do not explicitly model the competition between hotels and Airbnb. The hedonic models of the Airbnb price and occupancy rate are estimated conditional on the observed competitive landscape between hotels and Airbnb. The implicit assumption is that hotels in the counterfactual analysis follow the same strategy as in the observed scenario. The equilibrium we solve for can be regarded as a partial equilibrium without hotel responses. We believe that the trade-off between long-term rental and Airbnb is the first-order effect for property owners who are the key players in studying Airbnb's impact on the long-term rental market. In addition, hotels do not appear to have responded to Airbnb in practice according to Li and Srinivasan (2019), who study competition between hotels and Airbnb. In the future, when hotels have systematically responded to Airbnb, researchers can incorporate hotel responses into our framework.

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Table 9: Switching Patterns in the AHS Data Set

(a) Switching Patterns: Cell Percentages (%)

		2017 Airbnb	2017 Vacant	2017 Long-term rental	*Row Total*
2015	Airbnb	0.15	0.37	0.10	*0.63*
	Vacant	0.30	5.63	1.74	*7.67*
	Long-term rental	0.35	1.47	89.87	*91.70*
	Column Total	*0.80*	*7.48*	*91.72*	*100.00*

(b) Switching Patterns: Row Percentages (%)

		2017 Airbnb	2017 Vacant	2017 Long-term rental	*Row Total*
2015	Airbnb	24.19	59.56	16.25	*100.00*
	Vacant	3.86	73.46	22.68	*100.00*
	Long-term rental	0.39	1.61	98.01	*100.00*

(c) Switching Patterns: Column Percentages (%)

		2017 Airbnb	2017 Vacant	2017 Long-term rental
2015	Airbnb	18.92	4.99	0.11
	Vacant	36.87	75.30	1.90
	Long-term rental	44.21	19.71	97.99
	Column Total	*100.00*	*100.00*	*100.00*

Online Appendix

A. Evidence of Switching

As discussed in Footnote 11 of the paper, vacant units that are rented for "3 to 7 nights" and "8 or more nights" in the AHS data are potentially Airbnb listings and overlap with entire place listings on Airbnb. We flag these potential Airbnb listings in the AHS data set as choosing the Airbnb option in a year. The remaining vacant properties chose the vacant option. The long-term rental properties chose the long-term rental option. This means that we can observe properties that choose all three options (long-term rental, Airbnb, and vacant) within the AHS data set. Given the longitudinal nature of the AHS data set, we can present some switching patterns over time at the property level within the AHS data set.

Table 9a presents the switching patterns for properties that we observe data for two years. The rows represent the option that a property chose in 2015 and the columns represent the option that the same property chose in 2017. The number in each cell represents the percentage of properties that have the corresponding option combination. For instance, the first cell suggests that 0.15% of the properties chose Airbnb in 2015 and chose Airbnb in 2017. The percentages of all cells add up to 100%. The table shows that there were switching behaviors among all three options, suggesting that switching exists in our data set.

Besides presenting the switching patterns in terms of the cell percentages in Table 9a, we also present the switching patterns in terms of the row percentages in Table 9b and the column percentages in Table 9c. The row percentages of cells in the same row add up to 100%. The column percentages of cells in the same column add up to 100%. The row and column percentages are useful because these switching patterns in the data can relate to the two measures of switching behaviors we use in Section 7.2 of the paper:

(1) Percentage of reduction in rental supply due to Airbnb. This measure corresponds to the row percentage of the cell "2015 long-term rental -> 2017 Airbnb" in Table 9b because it represents the percentage of long-term rental units that switched to Airbnb. We find that this number is 0.39% in the table. This suggests that the percentage of rental reduction due to Airbnb is -0.39% in the data, which is comparable to the model-predicted ones in the paper (between -0.16% and -1.46%).

(2) Cannibalization rate or the fraction of Airbnb listings that come from switching from long-term rental. This measure corresponds to the column percentage of the cell "2015 long-term rental -> 2017 Airbnb" in Table 9c because it represents the percentage of Airbnb units that come from switching from long-term rental. We find that this number is 44.21% in the data, which is comparable to the model-predicted ones in the paper (between 10.4% and 48.8%).

The fact that the data-generated switching patterns are comparable to our model-predicted ones boosts our confidence that our model is able to obtain reasonable estimates of cannibalization effect and switching. It serves as a validity check on the effect magnitudes we obtain from the model. One caveat of the data-generated switching patterns is that they only reflect switching to/from Airbnb entire place listings and do not include Airbnb private room listings. The reason is that the approach we use to identify potential Airbnb units in AHS can only identify entire place listings as discussed in Footnote 11. Given that the data patterns only include part of Airbnb listings, the implied relative sizes of switchers and non-switchers may be inaccurate. However, the absolute number of switchers is accurate: while non-switchers can be either entire place listings or private room listings, switchers can only be entire place listings (as private room listings cannot choose long-term rental and would not be switchers from long-term rental). The data patterns include all entire place listings. Therefore, they include all the switchers and serve the goal of showing that switching exists in the data, which helps the identification of switching.

B. Restricting the Number of Days to be Integers

Let $u(s) \equiv \frac{p_{it}^A \phi_{it}^A}{\bar{s}(\exp(s/\bar{s})-\exp((s-1)/\bar{s}))} - (\bar{c}^{Av}+\beta^{Av}X_{it}^{Av}+\xi_{mt}^{Av})$ and $l(s) \equiv \frac{p_{it}^A \phi_{it}^A}{\bar{s}(\exp((s+1)/\bar{s})-\exp(s/\bar{s}))} - (\bar{c}^{Av}+\beta^{Av}X_{it}^{Av}+\xi_{mt}^{Av})$. Taking into account the fact that the number of days to list the property on Airbnb is integer, the second-stage probabilities are

$$\Pr\left(s_{it}=0\right)=\Pr\left(\Pi_{it}^{A}(0)>\Pi_{it}^{A}(1)\right)=\Pr\left(\epsilon_{it}^{Av}>l(0)\right)=1-\Phi\left(\frac{l(0)}{\sigma_2}\right)$$

$$\begin{aligned}\Pr\left(s_{it}=s\ (s=1,2,...,\bar{s}-1)\right)&=\Pr\left(\Pi_{it}^{A}(s)>\Pi_{it}^{A}(s-1)\text{ and }\Pi_{it}^{A}(s)>\Pi_{it}^{A}(s+1)\right)\\&=\Pr\left(l(s)<\epsilon_{it}^{Av}<u(s)\right)=\Phi\left(\frac{u(s)}{\sigma_2}\right)-\Phi\left(\frac{l(s)}{\sigma_2}\right)\end{aligned}$$

$$\Pr\left(s_{it}=\bar{s}\right)=\Pr\left(\Pi_{it}^{A}(\bar{s})>\Pi_{it}^{A}(\bar{s}-1)\right)=\Pr\left(\epsilon_{it}^{Av}<u(\bar{s})\right)=\Phi\left(\frac{u(\bar{s})}{\sigma_2}\right)$$

Given the optimal number of days to list the property on Airbnb, the ex ante monthly profit from Airbnb hosting is

$$E\left[\Pi_{it}^{A}(s_{it}^{*})\right]=\left[\int_{-\infty}^{\infty}\Pi_{it}^{A}\left(s_{it}^{*}\right)f\left(\epsilon_{it}^{Av}\right)d\epsilon_{it}^{Av}\right]$$

where the integral is expanded as

$$\begin{aligned}\int_{-\infty}^{\infty}\Pi_{it}^{A}\left(s_{it}^{*}\right)f\left(\epsilon_{it}^{Av}\right)d\epsilon_{it}^{Av}=&\int_{l(0)}^{\infty}\Pi_{it}^{A}\left(0\right)f(\epsilon_{it}^{Av})d\epsilon_{it}^{Av}\\&+\int_{l(1)}^{u(1)}\Pi_{it}^{A}\left(1\right)f(\epsilon_{it}^{Av})d\epsilon_{it}^{Av}\\&+...\\&+\int_{l(\bar{s}-1)}^{u(\bar{s}-1)}\Pi_{it}^{A}\left((\bar{s}-1)\right)f(\epsilon_{it}^{Av})d\epsilon_{it}^{Av}\\&+\int_{-\infty}^{u(\bar{s})}\Pi_{it}^{A}(\bar{s})f(\epsilon_{it}^{Av})d\epsilon_{it}^{Av}\end{aligned}$$

Here, the first term for the interval with $s_{it}^{*}=0$ is zero:

$$\int_{l(0)}^{\infty}\Pi^{A}(0)f(\epsilon_{it}^{Av})d\epsilon_{it}^{Av}=\int_{l(0)}^{\infty}0\cdot f(\epsilon_{it}^{Av})d\epsilon_{it}^{Av}=0$$

The terms for the intervals with $s_{it}^{*}=s\ (s=1,2,...,\bar{s}-1)$ is computed as:

$$
\begin{aligned}
&\int_{l(s)}^{u(s)} \left[p_{it}^A \phi_{it}^A s - c_{it}^{Av} \bar{s} \left(\exp\left(\frac{s}{\bar{s}}\right) - 1\right)\right] f(\epsilon_{it}^{Av}) d\epsilon_{it} \\
&= \left[p_{it}^A \phi_{it}^A s - \bar{s}\left(\bar{c}^{Av} + \beta^{Av} X_{it}^{Av} + \xi_{mt}^{Av}\right) \left(\exp\left(\frac{s}{\bar{s}}\right) - 1\right)\right] \int_{l(s)}^{u(s)} f(\epsilon_{it}^{Av}) d\epsilon_{it}^{Av} \\
&\quad - \left[\bar{s}\left(\exp\left(\frac{s}{\bar{s}}\right) - 1\right)\right] \int_{l(s)}^{u(s)} \epsilon_{it}^{Av} f(\epsilon_{it}^{Av}) d\epsilon_{it}^{Av} \\
&= \left[p_{it}^A \phi_{it}^A s - \bar{s}\left(\bar{c}^{Av} + \beta^{Av} X_{it}^{Av} + \xi_{mt}^{Av}\right) \left(\exp\left(\frac{s}{\bar{s}}\right) - 1\right)\right] \left[\Phi\left(\frac{u(s)}{\sigma_2}\right) - \Phi\left(\frac{l(s)}{\sigma_2}\right)\right] \\
&\quad - \left[\bar{s}\left(\exp\left(\frac{s}{\bar{s}}\right) - 1\right)\right] \left[-\frac{\sigma_2}{\sqrt{2\pi}}\left(\exp\left(-\frac{u(s)^2}{2\sigma_2^2}\right) - \exp\left(-\frac{l(s)^2}{2\sigma_2^2}\right)\right)\right]
\end{aligned}
$$

For the last term for the interval with $s^* = \bar{s}$, recall that $\Pi_{it}^A(\bar{s})$ is bounded by the maximum possible profit, $p_{it}^A \bar{s}$.

$$
\begin{aligned}
&\int_{-\infty}^{u(\bar{s})} \Pi_{it}^A(\bar{s}) f(\epsilon_{it}^{Av}) d\epsilon_{it}^{Av} \\
&= \int_{-\infty}^{\frac{p_{it}^A(\phi_{it}^A - 1)}{\exp(1)-1} - (\bar{c}^{Av} + \beta^{Av} X_{it}^{Av} + \xi_{mt}^{Av})} \left[p^A \bar{s}\right] f(\epsilon_{it}^{Av}) d\epsilon_{it}^{Av} \\
&\quad + \int_{\frac{p_{it}^A(\phi_{it}^A - 1)}{\exp(1)-1} - (\bar{c}^{Av} + \beta^{Av} X_{it}^{Av} + \xi_{mt}^{Av})}^{u(\bar{s})} \left[p_{it}^A \phi_{it}^A \bar{s} - c_{it}^{Av} \bar{s}\left(\exp(1) - 1\right)\right] f(\epsilon_{it}^{Av}) d\epsilon_{it}^{Av}
\end{aligned}
$$

where the integrals are computed similarly as in the other terms for the intervals with $s_{it}^* = s$ $(s = 1, 2, ..., \bar{s} - 1)$.

C. Hedonic Regression Results

Table 10 shows the hedonic regression results for rent and rental occupancy rate. Table 11 shows the hedonic regression results for Airbnb price and occupancy rate. The error terms are clustered at the metro area level. The R-squared value for Airbnb occupancy rate is relatively low, which may be due to a large variation in the occupancy rate over time even within the same property. In fact, Airbnb occupancy rate seems to be quite random at the individual property level. Analysis of within- and across-property variation shows a large within-property variation across months, and including market-specific month fixed effects in the regression does not explain the large within-property variation. However, the model-predicted Airbnb occupancy rate is consistent with average occupancy rate for each property. In other words, hosts are, on average, correct in predicting their occupancy rates, which is more important when making first-stage decisions.

Table 10: Hedonic Regression: Rent and Rental Occupancy

DV:	Rent		Rental Occupancy	
Constant	1,186***	(42.36)	0.848***	(0.137)
Rental Supply	-100.6***	(29.81)	-0.00182***	(0.00060)
Rent	–		-0.000178***	(0.000015)
Metro Area - Year FE	Yes		Yes	
Demographics				
Age				
35-65	-55.88***	(9.402)	-0.0346***	(0.00731)
Over 65	-147.0***	(15.14)	0.0733***	(0.0178)
Education				
High School Grad	-31.83***	(11.05)	0.224***	(0.00549)
Bachelor's	155.3***	(12.96)	0.275***	(0.0185)
Marital Status				
Never Married	-22.79**	(10.71)	0.112***	(0.00476)
Married Now	-33.68***	(10.65)	0.118***	(0.00553)
Gender				
Male	-16.61**	(8.181)	0.0483***	(0.00358)
Race				
Black	-184.2***	(10.06)	0.00603	(0.0215)
Other	34.96***	(11.77)	-0.254***	(0.00593)
Origin				
Hispanic	-118.9***	(10.13)	0.0661***	(0.0142)
Household Income				
50K-100K	121.1***	(9.705)	0.0444***	(0.0144)
Over 100K	366.2***	(12.82)	0.0776*	(0.0423)
Property Characteristics				
# of Bedrooms				
1	13.28	(30.21)	-0.00994	(0.0113)
2	72.94**	(33.65)	0.0166	(0.0150)
3	114.0***	(34.60)	0.0545***	(0.0183)
4	80.86*	(42.66)	0.0519***	(0.0183)
5+	122.0**	(58.12)	0.0746***	(0.0257)
# of Bathrooms	65.85***	(5.018)	0.00590	(0.00779)
# of Rooms	19.23***	(6.078)	-0.00495	(0.00316)
# of Amenities	37.47***	(3.565)	0.0132***	(0.00450)
Property Type				
House	-131.5***	(12.52)	-0.0176	(0.0158)
Other	-478.6***	(49.28)	-0.0337	(0.0580)
# of Units in the Structure				
2	-145.5***	(15.91)	-0.0306*	(0.0177)
3-4	-111.3***	(14.38)	-0.0118	(0.0139)
5-9	-97.88***	(13.30)	-0.00866	(0.0123)
10+	-138.1***	(13.23)	-0.0116	(0.0166)
Unit Age	-6.892***	(0.608)	0.000196	(0.000823)
Unit Age Squared	0.0507***	(0.00532)	-3.35e-06	(6.15e-06)
N	15,670		15,670	
R^2	0.396		0.578	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. The rental supply is in million units. The baseline demographics group is age under 35, education below high school, income below 50k, female, white, non-Hispanic origin, and widowed/divorced/separated.

Table 11: Hedonic Regression: Airbnb Price and Occupancy Rate

DV:	Logged Airbnb Price		Airbnb Occupancy	
Constant	4.844***	(0.0146)	2.645***	(0.120)
Airbnb Supply	-0.0196***	(0.00166)	-0.0207***	(0.00147)
Logged Airbnb Price	–		-0.425***	(0.0247)
Metro Area - Year FE	Yes		Yes	
Metro Area - Month FE	Yes		Yes	
Demographics				
Age	0.00862***	(8.51e-05)	0.00363***	(0.000225)
Household Income	0.00195***	(1.21e-05)	0.000706***	(4.93e-05)
Education				
Bachelor's	-0.135***	(0.00591)	-0.306***	(0.00594)
High School Grad	-0.438***	(0.00761)	-0.654***	(0.0125)
Marital Status				
Married Now	-1.308***	(0.00952)	-0.702***	(0.0333)
Never Married	-0.185***	(0.0103)	-0.0188*	(0.00969)
Gender				
Male	0.314***	(0.00628)	0.0813***	(0.00935)
Race				
Black	-0.364***	(0.00235)	-0.129***	(0.00922)
Other	-0.0924***	(0.00282)	-0.0697***	(0.00328)
Origin				
Hispanic	-0.241***	(0.00242)	-0.0873***	(0.00629)
Property Characteristics				
# of Bedrooms				
1	0.118***	(0.00129)	0.00443	(0.00311)
2	0.375***	(0.00114)	0.116***	(0.00933)
3	0.578***	(0.00145)	0.207***	(0.0143)
4	0.733***	(0.00207)	0.284***	(0.0182)
5+	0.692***	(0.00297)	0.252***	(0.0173)
# of Bathrooms	0.0965***	(0.000513)	0.00371	(0.00243)
# of Amenities	0.0132***	(0.000170)	0.0271***	(0.000356)
Property Type				
House	0.0201***	(0.000775)	0.0329***	(0.000815)
Other	0.0477***	(0.000678)	0.0764***	(0.00131)
Room Type				
Private/Shared	-0.515***	(0.000645)	-0.290***	(0.0127)
Airbnb-related metro variables				
Airbnb history (months)	0.00207***	(0.000340)	0.000610**	(0.000288)
Air passengers (in millions)	-0.0191***	(0.00536)	0.0531***	(0.00448)
Google search trend	0.00107***	(8.89e-05)	-0.00349***	(7.85e-05)
N	2,917,491		2,917,491	
R^2	0.525		0.139	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. The baseline demographics group is education below high school, female, white, non-Hispanic origin, and widowed/divorced/separated.

Harvard Business Review

Economics

Research: Restricting Airbnb Rentals Reduces Development

by Ron Bekkerman, Maxime C. Cohen, Edward Kung, John Maiden, and Davide Proserpio

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HBR Staff/stuartbur/Getty Images

Summary. Much has been written about the harm caused by short-term rental (STR) platforms such as Airbnb. By driving up demand for housing, these platforms can result in higher rents and house prices, thus potentially driving out long-time residents. However, the authors' new... **more**

It's well-known that one of the downsides of short-term rentals (STRs) is that they can reduce the availability of housing for long-term residents, thus driving up both rents and house prices for locals. In a previous study, we found that home-sharing through

Airbnb alone is responsible for about 20% of the average annual increase in U.S. rents, leading many policymakers to take an understandably aggressive approach to regulating STRs. For example, New York City has made it outright illegal to rent an apartment for fewer than 30 days in most buildings.

However, while this short-term impact is well established, the longer-term impact of the last decade's boom in STRs is less clear. Could the immediate harm of services like Airbnb to the local economy be offset or even outweighed by the long-term increase in demand they create?

To explore this question, we conducted a large-scale study analyzing a decade's worth of Airbnb listings and residential permit applications in the U.S. Residential permits are necessary for both new construction projects and substantial changes to existing structures, which makes them an effective way to measure the local economic growth that results from owners investing significantly in developing their properties. Based on this dataset, we identified a clear connection between STRs and residential permits: On average, a 1% increase in Airbnb listings led to a 0.769% increase in permit applications, suggesting that Airbnb can play a major role in supporting local real estate markets and thus boosting local tax bases. Given these findings, it follows that restricting STRs can have a significant, negative impact on local economic activity.

Of course, this is not to say that the negative economic impacts identified in our prior work are irrelevant. In the next part of our study, we took a more granular approach in an attempt to measure the direct impact of various STR regulations and identify strategies that can help communities reap the long-term benefits of the economic activity generated by these rentals while minimizing the short-term harm to residents.

To dig deeper into the underlying market forces at play, we divided our analysis into two parts: a nationwide examination of Airbnb's impact across 15 major U.S. metropolitan areas from 2008 to 2019, and an in-depth exploration of the effects of different local restrictions within Los Angeles County. The national study ensured our findings were applicable across diverse geographic and demographic settings, while the detailed look at LA offered specific insights into the on-the-ground impact of different policies. In addition, it's worth noting that STR regulations were rolled out in the different cities at various points between 2012 and 2019, enabling us to avoid muddying our findings with factors specific to any particular city or time period.

In the first part of our analysis, we looked at 2.9 million residential permit applications, 750,000 Airbnb listings, and 4 million residential sales transactions across the country. The main limitation to expanding this beyond the 15 cities we looked at was access to residential permit application data, since in general, only larger metropolitan areas in the U.S. share their permit data publicly. Public tax data and sales records, however, were easily obtained from data aggregators, as was Airbnb listing data, which we cross-checked with several overlapping sources.

We then used a popular research design known as "difference-in-differences" to measure the causal impact of STR regulations on economic activity. We compared both Airbnb listings and residential permit applications in the three years before and after an STR restriction was passed in a given neighborhood, and then averaged these effects over all the neighborhoods in our study. Our analysis identified a clear downward trend in both listings and permits after a regulation was enacted: Airbnb listings fell by an average of 21%, and residential permits fell by an average of 10%.

The second part of our analysis zoomed in to focus on these effects within a single metropolitical area. We chose to look at Los Angeles County because it has a uniquely large, interconnected housing and labor market, with many independent jurisdictions and regulations coexisting side by side. Specifically, only 18 of LA's 88 municipalities have STR regulations, enabling us to perform direct comparisons between areas with STR regulations and their unregulated next-door neighbors. We focused our analysis on residential permits within a kilometer of a border between regulated and unregulated municipalities, in order to maximize the chances that the trends we identified were purely due to the difference in STR restrictions, rather than other, external factors that may have incentivized residential construction on one side or the other. Furthermore, in addition to general residential permit applications, we tracked permit activity for a category known as accessory dwelling units (ADUs) — that is, additions to existing homes, which are often especially well-suited for renting.

The results of this analysis were conclusive: On the sides of these borders without STR regulations, there were 9% more non-ADU permit applications and 17% more ADU permit applications than on the sides with restrictions. Clearly, demand for STRs has been driving the creation of extra housing capacity in LA, and it's been especially driving growth for housing that is suitable for home-sharing (i.e., ADUs).

In the final part of our study, we explored the relationship between permit applications and residential property values, which are associated with cities' property tax revenues. We looked at residential properties in our nationwide dataset that were sold during our sample period, and we found that those with a permit application between sales (i.e., those whose owners invested in improving their homes before selling them, potentially in order to meet STR demand) sold for an average 38% more than those without a permit application. Since STR regulations decrease the number of permit applications which in turn stymies growth in property values, we conservatively estimate that for the 15 cities we studied, STR restrictions reduced property values by a total of $2.8 billion and tax revenues by $40 million per year.

Of course, this is not to suggest that unregulated growth is the answer. While higher property values can increase cities' tax revenues which can then be reinvested into local communities, they can also lead to issues related to housing affordability, including pricing out existing residents or preventing new residents from entering these neighborhoods. But our research illustrates that with the right policy approach, STRs can be leveraged as a tool to encourage local real estate development and economic growth.

As such, rather than enforcing blanket restrictions that hinder growth, we recommend creating targeted policies that meet local needs. For example, a study of real estate activity in Chicago showed that encouraging STR development for properties in distressed neighborhoods and then turning those properties into Airbnb rentals fostered parallel development in nearby retail properties, creating jobs and adding value to the entire community. As development spurs growth, policies could be implemented that would set aside a portion of the resulting increased tax revenue to fund affordable housing for local residents. Similarly, to address gentrification concerns, the total amount of space available for STR use could be capped at a percentage of available housing capacity, thus encouraging the development of long-term housing alongside STRs.

Ultimately, our research highlights the importance of taking a nuanced approach to STR regulation. As with many fraught policy decisions, the main challenge that regulators face is to balance residents' shorter-term needs with the longer-term economic wellbeing of the community. There are no easy answers — but any effective solution will have to acknowledge the very real economic downsides of restricting what people can do on their property.

RB

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MC

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Deseret News

Where Airbnbs, VRBOs are having an outsized impact on Utah's housing market

By Katie McKellar
Jun 30, 2022, 4:15pm PDT

A newly constructed condo in Park City is pictured on Thursday, June 30, 2022. Short-term rentals, much like Airbnbs, are having a big impact on Utah's housing market.
Mengshin Lin, Deseret News

As short-term rental sites like Airbnb and VRBO have exploded in popularity, so have short-term rental properties themselves, especially in vacation destination areas.

In Utah — where skiers flock in the winters and other outdoor enthusiasts like hikers, bikers and climbers swarm in the summers — these short-term rental properties are indeed having an outsized impact on the housing market, housing availability and, yes, housing affordability.

In particular, these rental properties have eaten up a striking share of housing units in one of Utah's most popular resort communities, the ski mecca of Park City. Here, short-term rentals made up nearly 43% — almost half — of Park City's housing stock in 2020.

Almost half. Let that sink in.

That's according to a new report published Wednesday by the University of Utah's Kem C. Gardner Policy Institute's senior research fellow Dejan Eskic, who specializes in housing research.

In his report, Eskic noted short-term rentals accounted for a small percentage — 1.6% — of the state of Utah's total housing units in 2021. But even though it's a "relatively low" figure, Eskic points out the distribution of short-term rentals in Utah is uneven and is impacting some areas more than others.

And that's certainly not helping the state's affordability issues.

Utah was facing a housing shortage even before the COVID-19 pandemic sent the U.S. housing market into a frenzy — especially in the West. And now, as mortgage rates tick up, more than 70% of Utahns have been priced out of the state's median-priced home, which topped $500,000 statewide in February. That figure is even higher in Salt Lake and Utah counties.

"Academic research indicates a relationship with increasing (short-term rental) supply leading to a decrease in affordability and housing options as supply is occupied by visitors rather than full-time residents," Eskic wrote.

The aim of the report wasn't to draw "causality for housing prices," Eskic wrote. Rather, it seeks to give Utah policymakers an account of the size of the short-term rental market and how it relates to total housing supply.

Consider some of Eskic's top findings:

- **Utah's short-term rentals are growing.** In 2019, there were 14,782 short-term rentals listed in Utah. That number jumped to 18,743 in 2021, an increase of 26.8% in two years.

- **Entire home rentals are gaining popularity.** In 2019, there were 12,868 entire homes listed. That went up to 17,236 in 2021. During this same time period, private room listings dipped from 1,914 in 2019 to 1,507 in 2021.
- **Utah's short-term rentals are unevenly distributed.** In sheer numbers, they're most concentrated in five counties: Summit County (home to Park City), Washington County (home to sunny St. George), Salt Lake County (Utah's most populous county and home to Salt Lake City), Rich County (home to Bear Lake) and Grand County (home to Moab and Arches National Park).

But other, smaller communities also see higher percentages of short-term rentals.

Where are Airbnb, VRBO's most concentrated in Utah?

Here's a top-five ranking of counties with the largest shares of short-term rental properties in 2021, according to Eskic's research:

1. **Summit County**: 6,043 short-term rentals make up 23.3% of the area's total housing units.
2. **Grand County:** 1,026 short-term rentals make up 19.3% of the area's total housing units.
3. **Rich County:** 524 short-term rentals make up 16.5% of the area's total housing units.
4. **Kane County:** 493 short-term rentals make up 8% of the area's total housing units.
5. **Garfield County**: 219 short-term rentals make up 6.2% of the area's total housing units.

By sheer numbers, here's a ranking of the top five counties with the highest numbers of short-term rentals in 2021, according to the report:

1. **Summit County**: 6,043 short-term rentals make up 23.3% of the area's total housing units.
2. **Salt Lake County:** 3,420 short-term rentals make up 0.7% of the area's total housing units.
3. **Washington County:** 2,803 rentals make up 3.5% of the area's total housing units.
4. **Grand County:** 1,026 short-term rentals make up 19.3% of the area's total housing units.

5. **Utah County**: 879 short-term rentals make up 0.4% of the area's total housing units.

Drilling down to city-level data, here are the top five cities with the largest shares of short-term rentals in 2021. Note that only Thompson Springs, a small community outside of Arches National Park and near Moab, outpaces Park City, which has a much larger number of short-term rentals.

1. **Thompson Springs, Grand County:** Nine short-term rentals, making up 47.8% of the area's housing units.
2. **Park City, Summit County:** 3,922 short-term rentals, making up 42.9% of the city's total housing units.
3. **Brian Head, Iron County**: 491 short-term rentals, making up 39.7% of the city's total housing units.
4. **Snyderville, Summit County**: 1,764 short-term rentals, making up 35.2% of the city's total housing units.
5. **Garden City, Rich County (by Bear Lake):** 436 short-term rentals, making up 25.7% of the city's total housing units.

https://www.thepeterboroughexaminer.com/news/newly-renovated-apartments-appear-on-airbnb-in-peterborough-are-short-term-rentals-affecting-long-term/article_046e1e28-5182-5c70-9225-c6458d395fe0.html

Home / News

NEWS

Newly renovated apartments appear on Airbnb in Peterborough, are short-term rentals affecting long-term tenants?

‘Airbnbs are like predators’ says housing analyst, adding they take valuable long-term apartments off-line

As more Airbnbs take up residency, is there room for short-term rentals in Peterborough's tight housing market?

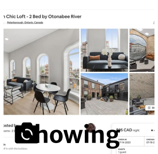
PETERBOROUGH This Week.

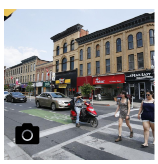
By **Taylor Clysdale** Peterborough This Week

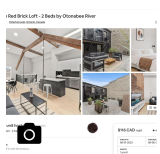
Jul 28, 2023

Article was updated Aug 1, 2023

Listings on Airbnb show units inside the GS Lofts, which were recently renovated by SummersandCo. The developer's owner says he isn't operating the units, but he is aware of them. - Screenshot from Airbnb







There are multiple listings on Airbnb for apartments described as a "brand-new boutique loft," with at least four listings in Peterborough appearing under same account for the same building.

That building, the GS Lofts, was recently renovated during the COVID-19 pandemic. It's redevelopment was highly anticipated as one of the first in a wave of revitalization projects downtown.

"We don't have an Airbnb in there," said Rick Summers, owner of the building and a redeveloper of older properties. "We just rent to an individual tenant. (But) we do know there is (an Airbnb unit)."

So while he's not operating short-term rentals out of his building, someone else is. And according to housing analyst Paul Armstrong that hurts the market for long-term renters.

"I haven't seen any corroborating data, but there's no doubt Airbnbs are putting more pressure on the market," said Armstrong, author of the annual Housing is Fundamental report for the United Way Peterborough and District.

The City of Peterborough says there is no permitting process, nor any data available, for short-term rentals in the city.

But Armstrong says for each unit converted into an Airbnb, that's more long-term units taken off-line. "It makes the availability of apartment stocks even less than what it should be," he explained. "Airbnbs are like predators."

Summers says, for him, it's important buildings are full and making money for their owners. Having more income means building more units, which means more room for everyone.

"If an apartment is empty for two, three months that's lost revenue that you won't get back," said Summers. "If there's no cash flow and it doesn't pay for the cost to construct it (and), you won't have any long-term units."

Peterborough This Week connected with a person running the account listing for at least four units in Summers' building. The person said they would "co-ordinate with our team" for a response, but as of Friday, July 28, they had still not connected for an interview.

When it comes to renting out his buildings, Summers' says "we look for a good, strong … financially good tenant that will take care of the place."

And that means catering to whatever the "supply and demand" is for units.

"The solution is to create housing units, which is our whole business model," said Summers, adding his company's goal is to "do our part" to add affordable housing stock, and make room for both long- and short-term tenants.

Because of that, the public should be advocating for more incentives for developers to refresh older buildings, he says.

Summers&Co., his company, specializes in "recycling old buildings," noting it also focuses on avoiding tearing down sites that would end up in landfill.

But if new units become short-term rentals, then it's not adding anything to the market for long-term renters, says Armstrong.

"If you look at the whole apartment stock, you have to take out Airbnbs and you can see how your availability starts to shrink," said the housing analyst. "It's another form of the financialization of housing."

Canada continues to treat housing as a commodity for profit, instead of a basic human right, he explains. And when that happens, some people go without roofs over their heads.

But it's clear there's a demand for short-term rentals, as evidenced not only in Peterborough, but in larger urban centres like Toronto.

"Peterborough has a lot of summer activities, it has quite a few tourists going through the Kawarthas," noted Summers.

With that said, Summers says he still wants to rent out apartments and he doesn't want his buildings' sole purpose to be short-term rentals. "It's not like a hotel, we don't want to change the use or how the apartments function," he added.

Summers' company doesn't interact with the Airbnb users themselves, but instead with the person listed on the lease. If there's any issues, it's that individual who will potentially be evicted.

And there have been issues in the past with other units rented out for Airbnbs, he says.

"When you have a bunch of humans living together, it doesn't matter where they're from. But nothing dramatic like they're having parties every night, because they would just not be allowed to stay," he added.

There have been plenty of reports of problem Airbnb tenants across Ontario though. While there might not be any data in Peterborough about short-term rentals, in cities like Toronto there is a bit more information.

In 2017 the Canadian Centre for Policy Alternatives published a report asking for the regulation of short-term rentals "that should help curb the steep rise of quasi-hotel condos and nuisance short-term rentals in residential neighbourhoods."

According to the report, many of those units "belong to hosts that offer multiple listings" as well as tenants who often list units "illegally, without the consent of their landlords.

"When an entire property is listed as a short-term rental, this impacts the housing market — the protection of which is a primary concern in many jurisdictions," it added.

In 2021, Toronto opted to regulate short-term rentals, but issues still pop up of hosts with multiple units. In 2023 the courts decided short-term rental users don't qualify as tenants and don't have tenants' rights.

Another potential impact to the market is price. Short-term rentals create scarcity, which drives up rent prices, says Armstrong.

While having more room in the market would be great, as well as more affordable options, there just isn't a successful model for affordable housing for private developers, says Armstrong. It also doesn't help there isn't a solid definition of "affordable" so developers can have different interpretations of what that means.

The housing advocate agrees with Summers though, there does need to be government policy changes to support affordable housing. But the buck of that portfolio has been passed down from the federal government to the municipal governments, who lack the resources to do it properly.

To have a housing market with room for both long- and short-term renters, Armstrong says "you're just going to have to have more building. Even construction of purpose-built apartment buildings isn't keeping pace with demand, that's for sure," he added.

Summers says he sees that too, and he wants to see further intensification in Peterborough.

There is a lot of demand for those seeking to live and rent in downtown, he says. He has plans on renovating another two-storey building up the street at 385-391 George St., to add three more storeys and create 56 apartments, including affordable ones, plus five commercial units.

Downtown redevelopments intensify urban centres, but also raises property values of adjacent buildings, says Summers. It also brings new tenants downtown to spend money and support the local economy.

But it needs to be profitable for developers to make those units, he notes. And short-term rentals are filling apartments and making money.

"There wouldn't be more long-term — any units on the market, if it's not affordable to create them," he added. "It all comes down to the numbers."

Taylor Clysdale *covers municipal, provincial and federal politics for Peterborough This Week.You can follow him on* **Twitter** *@TaylorClysdale and reach him at* ***tclysdale@mykawartha.com.***

Read more about

INSIDER

Philadelphia could wipe out 85% of its Airbnbs and Vrbos. It's a sign of the growing backlash against short-term rentals.

Dan Latu Jul 19, 2023, 11:43 AM PDT

Philadelphia is enforcing a 2021 law to regulate short-term rentals. James Leynse/Getty Images

- **Philadelphia is enforcing a law that requires Airbnb and Vrbo hosts to license their properties.**

- **The city estimates nearly 1,700 short-term rentals are at risk of being removed from the platforms.**
- **How Philadelphia fares with regulation could impact how other cities proceed.**

Philadelphia is sending out notifications this month to Airbnb and Vrbo hosts with unlicensed properties stating they may have to cease renting out the pads.

The city is beginning to enforce a 2021 law that requires all short-term rentals to be licensed. Formerly, only units that rented out more than 90 days a year were required to be licensed, according to Philadelphia news station WHYY. In order to obtain a license, properties must meet certain requirements like being up to code and acquiring lead paint certificates.

By the city's own estimate, the crackdown could shut down 85% of all short-term rentals in the city — or nearly 1,700 units.

Hosts will have five business days after receiving the notice to either properly register their unit or convert to long-term stays of 30 days or more. If no action is taken, a host's listing will be removed, according to the city's Department of Licenses and Inspections.

Philadelphia is just one city contemplating the future of short-term rentals. Following the sector's explosive post-pandemic growth, residents across the country brought concerns over bad hosts or housing availability to local governments. How Philadelphia, the country's sixth-largest city, moves forward with regulation could set the tone for the way other cities follow suit.

Philadelphia will begin dual outreach, first to Airbnb and Vrbo to take down illegal listings, and then to hosts themselves.

"It's something that needs to be controlled and something that needs to be under supervision." Mayor Jim Kenney told Philadelphia radio station KYWNews. "And if people could act responsibly in their business dealings, we wouldn't have to do this. But that's not the case."

Councilmember Mark Squilla, who introduced the measure, told WHYY in 2021 that "by doing this we will have more control over the bad operators."

Airbnb, for its part, is working with the city. "For months Airbnb has worked closely with the City of Philadelphia to ensure they have the necessary tools and support to effectively enforce their current rules, including the ability to identify listings that may be unlicensed for removal," an Airbnb spokesperson told Insider. "We've also developed and distributed materials and messaging to our Hosts to make them aware of the new rules and how to comply."

Licenses are one of the variety of ways that cities and towns have attempted regulation, as opposed to a cap on the number of rentals or raising taxes on owners.

Ahead of the Super Bowl, Phoenix suburb Scottsdale, Arizona, enacted a similar license crackdown.

Scottsdale Councilmember Solange Whitehead told Insider that issues over short-term rentals had reached a boiling point. "We have people in cul-de-sacs that no longer have neighbors," she said.

In Bozeman, Montana, where short-term rentals nearly doubled during the pandemic, some locals have called for a permanent ban. Host Michael Rutkowksi told Insider that the town should start with enforcing the licensing requirements already on the books.

5 STEPS TO

Effective Short-Term Rental Regulation

A Simple Guide on Balancing the Interests and Well-being of Diverse Stakeholders

OPENGOV

Introduction

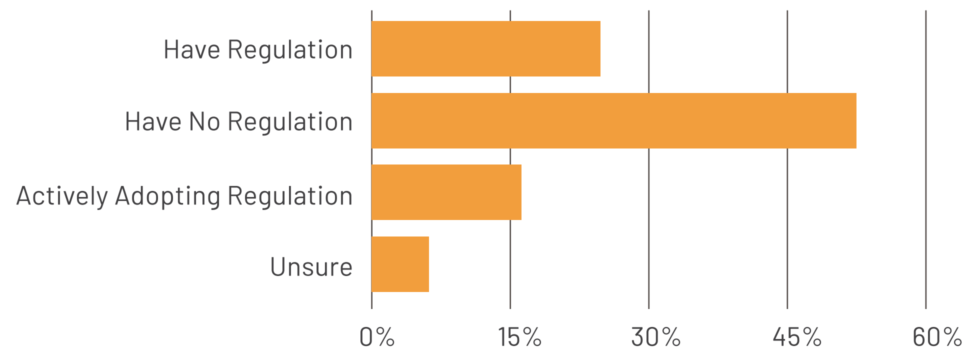
With the rise of Airbnb and other online rental platforms, short-term rental regulation has become an evolving and complex area for local governments.

While some may think it's only an issue in larger cities or tourist destinations, there are over 2,700 U.S. cities and counties with more than 50 short-term rental (STR) listings.*

It's a divisive issue for many communities, with clear arguments for both the benefits and costs of allowing more STRs. While some celebrate the additional income for residents and a boon to the local economy, others fear the degradation of their neighborhoods and lack of affordable housing.

Local government responses have ranged from no regulation to completely banning STRs. However, most communities have not yet figured out the best way to approach the issue. In a survey of 800 local government officials, only a quarter had rules in place, 53% stated having no rules, 16% were actively adopting new rules, and 6% were unsure.

Where Are Local Governments on Short-Term Rental Regulation



Source: Jeffrey B. Goodman and Host Compliance, Survey of Local Governments presented in "Webinar: The Best Practice Guide to Crafting a Short-Term Rental Ordinance/Bylaw"

If you are looking to develop and implement effective short-term rental regulation in your community, here is where to start.

**All cited statistics taken from Host Compliance and Jeffrey B. Goodman's presentation in:"Webinar: The Best Practice Guide to Crafting a Short-Term Rental Ordinance/Bylaw. Hosted by: iCompass*

STEP #1

Research

Before making decisions, you need to understand the context for your regulation. While easy to overlook, comprehensive research will be the foundation for successful short-term rental regulation.

Local Context

Begin the research process by getting a sense of the short-term rental market in your area.

Here are questions to consider while conducting this research:

- How many listings are there in your community?
- Where are current listings located? Where are the areas of concentration, if any?
- Where are the most bookings happening?
- What type, size, and occupancy levels of housing are offered?
- What are the range and average listing prices?

STEP #1

Map of current Airbnb listings in Seattle - insideairbnb.com

The website insideairbnb.com is a helpful resource for up-to-date data on current listings in larger cities. Smaller communities can gather data directly from airbnb.com and other online rental platforms.

It's also important to look at the local context indirectly related to short-term rental regulation.

- What is the picture of housing availability and affordability in your community?
- What are the other existing lodging options?
- How are socioeconomic demographics spread throughout the city?

Once you have a landscape of the STR market and pertinent local factors, you can start diving into other research areas.

STEP #1

Qualitative Data

As any local government official knows, research gets more complicated when you start gathering data from local stakeholders. Creating effective policy for a controversial issue like short-term rentals means managing this complexity, and ultimately coming out with a better understanding of your community's values.

Start by identifying the stakeholders:

- Who is concerned about the issue?
- Who might not know what's going on, but be inadvertently affected?
- What are their motivations? What are their fears?

STEP #1

Public comment forums will help get a pulse on residents' opinions. But frame the issue around planning objectives. When you make STRs a yes or no issue—are you for or against them?—it's too easy for stakeholders to hold opinions without considering compromise or community goals.

After you've identified relevant stakeholders, get a baseline on each group's motivations and fears.

- How are they currently affected by short-term rentals?
- What are they most concerned about—housing availability, neighborhood preservation, economic development?

Discussions will evolve throughout the regulation process, so initial conversations do not need to cover every concern. You will return to do a deeper stakeholder analysis after the initial research phase.

STEP #1

Policy Research

Do your due diligence on existing STR, bed and breakfast (B&B), and motel laws in your municipality. It's likely that at least some of the laws are outdated, and you'd be surprised at what you might find. As an example, one city had banned B&B's from serving breakfast due to the influence of a "brunch lobby".

Look at the state level as well. There are currently 10-15 states that regulate hotels and/or STRs. This changes the value for cities looking to invest in creating and enforcing new policies. If the money collected from fees and permits goes back to the state, it might not be worth the investment at a local level.

Additionally, some states have said municipalities cannot regulate STRs based on certain criteria (e.g. length of stay), and many states are changing laws rapidly, so keep up-to-date.

Lastly, in doing policy research, look beyond your local neighbors and your state. How are communities of similar size (or other important factors) around the country and around the world effectively addressing Airbnb regulation?

Amsterdam, one of Airbnb's closest partners, is currently discussing major reforms to their short-term rental regulations, trying to balance tourism and housing availability for residents.

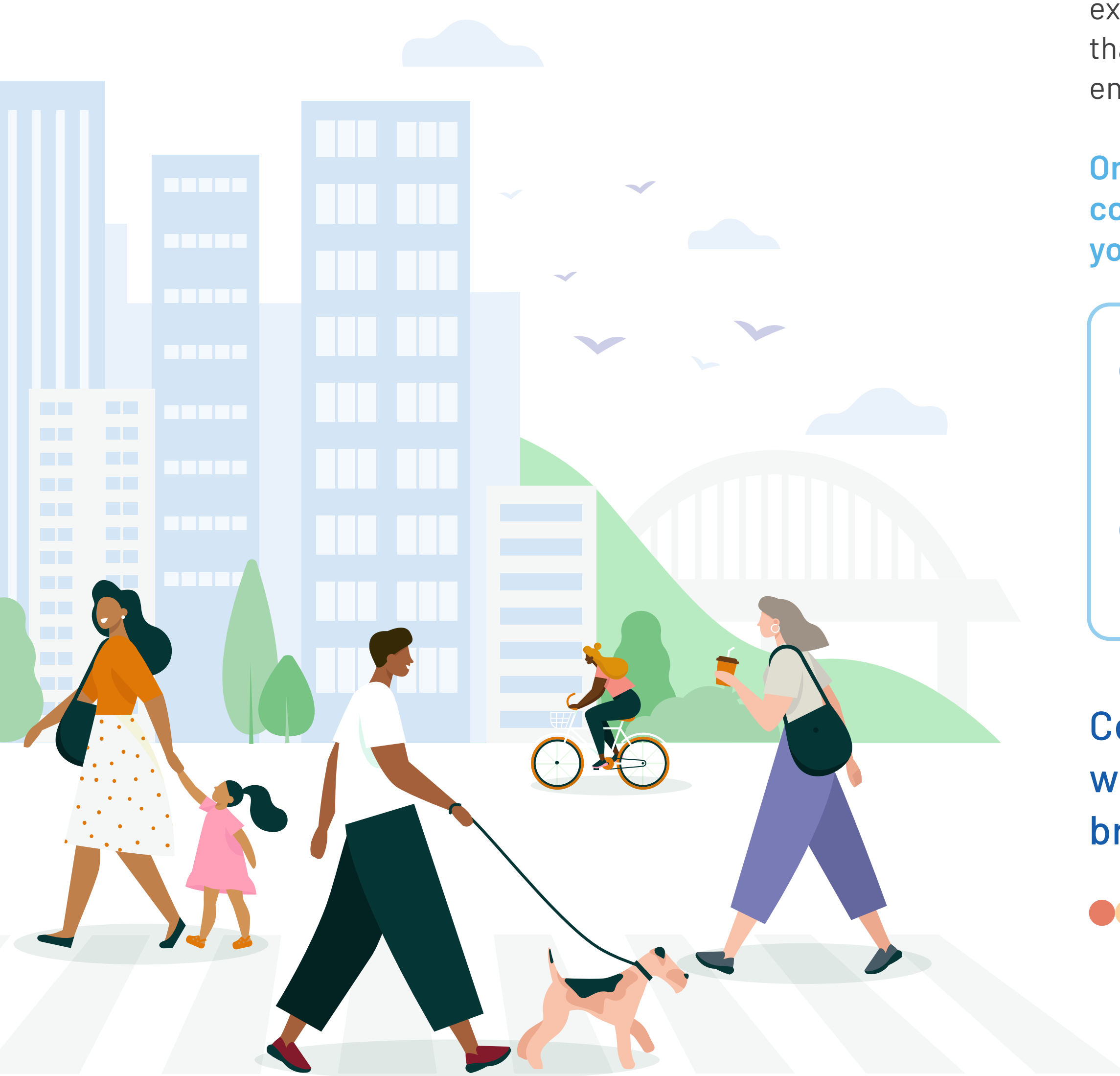
Enforcement Capabilities

Your policies will largely be shaped by what you can enforce. Take this into account early in the process, before you start publicly proposing things you don't have the capacity to enforce.

Consider these questions:

- What types of regulations do we have the ability to enforce with our current resources?
- What are we willing to spend on new resources?
- What kind of regulatory environment do we want to impose on our community?
- What is the input from those who would be responsible for enforcing new laws?

Are you thinking of requiring every rental unit to get an inspection with only one part-time inspector on staff? Is the police department willing to enforce a policy prohibiting excessive noise after a certain hour?



Access to data can also limit certain types of regulation. For example, San Francisco has outlawed STRs being rented more than 90 days of the year. This type of policy would be hard to enforce without reliable access to booking data.

On top of your government's enforcement capabilities, consider what kind of environment you want to create in your community.

- How will residents feel if the police begin making extra rounds in residential areas?
- Will additional inspections be invasive to surrounding residents?

Considering these scenarios will help you know what kinds of regulation options are realistic to bring to the table.

STEP #2

Framing the Issue

Framing the issue for productive discussion is key to managing diverse opinions and producing successful compromises.

Stakeholder Analysis

Public opinion matters, but so does the input of elected officials, relevant government departments, and local businesses.

Think about which government departments/responsibilities will be affected by new regulations (e.g. code enforcement, planning and zoning, permitting and licensing, finance, tax collection, police department, etc.).

STEP #2

Here are some basic questions to get you started:

- How will an increase in STRs affect each government department?
- Will any departments need new resources? Can the cost of new resources be covered by estimated increases in permitting and licensing fees?
- How many residents are actively concerned about the issue?
- Where do their fears and motivations overlap?
- Which businesses are for and against more STRs? How would an increase or decrease affect them?
- Where are areas of centralized commerce, entertainment, and tourism? How do we want STRs to affect their development?

Once you can map out the motivations, fears, and priorities for each interest group, you can move forward with the process. Understanding how policy changes may affect stakeholders and anticipating their reactions will help you judge the externalities of new regulation. More importantly, community voices will inform which planning objectives you choose to prioritize with short-term rental regulation.

STEP #2

Messaging

A stakeholder analysis will also help you come up with effective messaging, so people aren't surprised by new policy proposals. Remember to frame the issue beyond a simple yes or no.

Most communities will not impose full bans nor leave STRs unregulated, there will likely be a solution somewhere in between. Making sure stakeholders know they must be open to compromise will make discussion more productive.

Here are some foundational questions to help frame the issue:

- What problems are STRs actively causing in our community?
- What do we love and want to preserve about our community?
- How can STRs help us support our goals?
- How can policies address these issues and support these goals?

Allow anecdotes in public comment, but remain aware of biases. Most importantly, look for underlying patterns and the root causes of stakeholders' concerns.

STEP #3

Defining Planning Objectives

Some people will never compromise, and you must move past those voices to produce viable policies. The result of research and stakeholder analysis is a clear set of priorities to inform your planning objectives and therein your policy tactics.

Context and Values

Community context and values will vary. For some, housing availability is a main concern, while for others it may be neighborhood preservation and safety. It's important to communicate clearly about how you came to prioritize certain planning objectives, avoiding confusion and frustration with the process moving forward.

The table on page 16 shows a list of common STR policy objectives and corresponding regulation tactics.

Enforcement Capabilities

Remember that the ability to enforce a policy is the litmus test for what is realistic.

Always ask yourself:

- ? Can you enforce it legally and physically?
- ? Would it cause undue burden on the government's resources?

Use local context and community values to decide on planning objectives, and then check corresponding policy measures against enforcement capabilities. This will give you a tailored, realistic set of policy measures specific to your community.

STEP #3

Best Practices for Addressing Common Planning Objectives

These best practices were developed from Jeffrey B. Goodman's and Host Compliance's research on STR regulations in municipalities across the country. They are a good starting point, but no one knows the unique context of your community like you do. Don't be afraid to brainstorm creative policies that might work better in your area.

Common STR Policy Objectives	Best Regulatory Practices
Housing Availability	· Only allow permanent residents to operate STRs · Disallow rentals in subsidized housing
Neighborhood Preservation	· Set neighborhood quotas · Ban signs
Protecting Quality of Life	· Require adequate parking and garbage disposal · Require hosts to post noise ordinance · Require a local contact person
Economic Development	· Encourage hosting in certain areas and time frames
Safety	· Require physical safety and habitability inspections

STEP #4

Ordinance Drafting

Once you've done the research and prep work, it's time to dig into the details.

Planning discussions might happen in broader strokes, while ordinance drafting requires final decisions and precise language.

This is a good time to refer back to the laws already on the books, as well as example Airbnb policies from other municipalities you've gathered in your research.

Airbnb listings range from full houses to "camping in the backyard."

Short-term Rental Definition

You will need to specifically define short-term rentals beyond a "unit rented for less than 30 or 14 days."

In addition to length of stays, the definition should speak to:

- Who is allowed to host (this can have significant implications for planning objectives)? *Owners, renters, management companies, etc.*
- What types of units are allowed to be STRs (consider safety implications)? *Homes, bedrooms, accessory units, yards, etc.*
- What type of insurance is required for a STR property (this is to protect both the municipality and host)?

Effective short-term rental regulation is grounded in a clear definition. You want to avoid future questions in the enforcement process over whether something qualifies as a STR. If you are going to change your existing definition, take into account how current rental operations might change in status (e.g. will Airbnb listings be subject to the same regulations as traditional B&Bs?).

STEP #4

Land Use and Zoning

Use your STR land use and zoning policies to target your top planning objectives, like housing availability or economic development. For instance, if you want to preserve long-term housing options in certain areas, you can control density levels (i.e. only so many listings allowed in this area) or create buffers around units (i.e. no units within x distance of each other). Neighborhoods with a tight rental market may require harsher controls.

You also need to consider how to balance traditional lodging options with STRs.

- Should STRs populate the same areas as traditional lodging options? How will this affect businesses in those areas?
- How “commercial” does an STR have to be to reside in a commercial zone? Should STRs be allowed in residential areas?
- Should different types of STRs be zoned differently?

Prioritizing certain objectives means accepting tradeoffs. Ashland, Oregon prioritized neighborhood preservation in their Airbnb regulation, so they decided to keep all STRs near busy streets to avoid bothering residents. This might have the added effect of boosting the economy for local businesses.

However it also precludes many homeowners from being able to earn extra income through online rental platforms.

Unit Characteristics

Requiring units to have certain characteristics is not necessary, but it can help divert unwanted behaviors. Imposing bedroom/ occupancy limits and providing adequate trash and parking can help prevent large groups and parties from disturbing neighbors. Building, safety, and ADA codes help ensure listings are in legal compliance and in accordance with insurance policies. Remember that including specific unit characteristics will require additional inspections.

Permit fees can also help create the right balance of supply and demand for different types of units. Portland, Oregon requires different permits for rentals depending on the number of bedrooms (above 3 bedrooms is $3,000, and units with more than 5 bedrooms are not allowed). Scaling permit fees also helps the city collect revenue proportionate to the amount earned by hosts' listing prices.

Host Operation

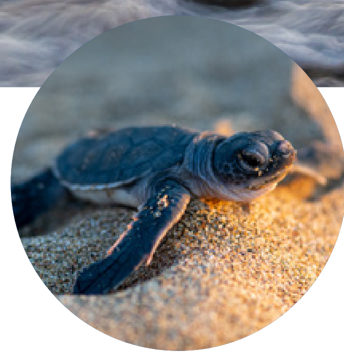
Some communities impose host operation regulations to keep hosts accountable and to keep neighbors apprised of STRs in their area.

Examples of this include:

- Requiring hosts to notify neighbors and allow a certain time period for neighbor input before booking a listing
- Requiring a host contact person to be available in case of emergency

Requiring a host contact person might affect who and how hosts are able to operate their STRs. If the contact has to be within a specific range of the listing, it might prevent homeowners from renting their houses while on vacation.

Alternatively, the policy might specify that the host contact could be someone other than the property owner (e.g. a relative or property manager), allowing hosts more flexibility around units (i.e. no units within x distance of each other). Neighborhoods with a tight rental market may require harsher controls.



Guest Requirements

Many communities also include guest requirements in Airbnb regulation, especially in residential areas.

Common areas to address include:

- Noise limits
- Pools & Spas (time restrictions for usage)
- Traffic limits
- Guest registration

Guests may also need to know community-specific information. For example, in one small Florida beach town, leaving the lights on at night is confusing for baby sea turtles looking for the ocean. So, short-term rental owners need to inform guests about lighting at night.

While this is a rare example, many communities will have unique considerations for new guests.

STEP #4

Permitting Process

Permitting is one of your most powerful tools in implementing effective short-term rental regulation and collecting revenue for your government. If you do not currently require permits or licenses for STRs, writing this part of your policy will probably be the most time-consuming. Incorporate feedback from government departments that will be involved in the permitting process, and remain realistic about your processing capabilities.

Ask these questions:

- Will short-term rentals rentals require a permit, license, or both?
- What are the main categories of STRs in your community (e.g. single homeowners, commercial properties, full-time vs. part-time listings)? Will these require different permits or licenses?
- Do you want to affect the supply and demand for STRs in the area? Is permitting the appropriate way to accomplish this goal?
- What is the range of listing prices, and how does that correspond with the way current lodging options are being taxed? Do you want to use flat or percentage fees?
- How easy are your permit applications to navigate and do you have the software to allow people to apply and pay online?
- Are you willing to invest in new permitting technology to increase your processing capacity?

STEP #4

Always consider the capacities of your permit office and staff before including permit requirements that will inundate them with more applications than they can handle.

Maybe some use types will require permits, while others will be exempt or have lower fees. For example, listings with bookings over a certain number of days per year may require a license, while occasional hosts only need a permit.

Some communities may decide to affect supply and demand by distributing a limited amount of STR permits. If you take this route, consider which types and listing locations will be willing to pay higher permitting and licensing fees. Always remember to refer back to your planning objectives as your guide.

STEP #4

Enforcement Process

Short-term rental regulation should include clear, actionable consequences to listing violations. This might involve imposing fees and suspending or rescinding permits. Violation fees should be proportionate to the amount charged on average listings in the area—if hosts are making $1,000/night they will not be discouraged by a $50 fee.

Think carefully about what consequences are appropriate for what kind of violations, and how consequences might affect the supply and demand of STRs in the long-term.

See the table below for example violations and corresponding consequences.

STEP #4

Short-Term Rental Violation Examples

Violation	Consequences
2+ Noise complaints	$50 fine
Failure to provide host contact	$75 fine
Improper insurance policy	$200 fine
3+ Violations	Permit suspension (6 months)
5+ Violations	Permit revocation

Make sure you have an accessible violation reporting process. Maybe this means creating a specific hotline or email address and advertising it on your website and social media. The ordinance—particularly violation consequences—should be clearly accessible for all hosts and residents, so everyone knows what the rules are. Creating a digestible regulation guide for hosts will save you headaches down the road.

There are countless contextual factors that will inform the right enforcement process for your community. As with all regulatory aspects, if you have having trouble deciding the right course of action on a topic, use your planning objectives and enforcement capabilities to guide you.

STEP #5

Incorporate Feedback

With any new policy, you will probably need to make adjustments as you see it play out in real time.

Provide channels for feedback from the stakeholders in your research. Additionally, some community members might have been unaware of early discussions, but have important input now that short-term rental regulation is directly affecting them.

Similarly, you can guess how the influx of permit and license applications will affect your departments, but you won't really know until they start coming in. Continuous lines of communication will help you know if you need additional resources (e.g. more staff, new software or hardware, etc.).

STEP #5

Advice for eliciting productive feedback:

- Remember to frame the policy around the planning objectives — avoid black and white stances
- Stay on topic
- Reference other comments so stakeholders understand they are compromising with other community members, not just the government

Depending on local laws, your ordinance might have a built-in expiration date, but you may want to make changes before the sunset. Keeping a record of stakeholder feedback and updating your research will help you reassess and make your ordinance more effective in addressing your community's goals.

Goodman emphasizes that there is no silver bullet to effective short-term rental regulation. Every community will need to assess their own local context and values before diving into this process. However, you are not in this alone. Use peer governments and expert research like Goodman's to help guide your process.

Steps to Effective Short-Term Rental Regulation

1. Research

- Local STR market
- Local context
- Identifying stakeholders
- Existing policies
- Enforcement capabilities

2. Frame the Issue

- Stakeholder analysis
- Tailored messaging

3. Define Planning Objectives

- Community values
- Matching planning objectives with policy measures

4. Draft the Ordinance

- Defining STRs
- Land use & zoning
- Unit characteristics
- Host operations
- Guest requirements
- Permitting process
- Enforcement process

5. Incorporate Feedback

- Provide channels
- Keep constructive
- Adjust regulations accordingly

By thoughtfully tackling this regulation area you are not only helping your residents achieve their goals as a community, but also paving the way for other governments looking to do the same thing. As technology and the sharing economy evolve, local governments will need to continue creating effective, adaptable regulation to match it.

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American Planning Association

Creating Great Communities for All

PAS MEMO

Short-Term Rentals: Regulation and Enforcement Strategies

By Jared E. Munster, PHD, AICP

Short-term rentals, home sharing, vacation rentals, Airbnb: regardless of what you call the concept, it is clear that the new sharing economy has worked its way into virtually every residential area in the country.

Short-term rentals (STRs) can be defined as the rental of all or part of a residential dwelling unit for a duration of occupancy of less than 30 days. They have raised the passions of free-market advocates who believe that the government should not regulate property rentals, as well as neighborhood activists who fear that STRs will degrade neighborhood cohesion and price out the very culture and experience visitors are venturing into neighborhoods to embrace. This conflict, as well as the challenge of attempting to regulate what is at its very core a residential occupancy, make the role of the planner critical in developing clear regulations that balance neighborhood concerns with practical limitations on how far local government can intervene in rental agreements for private property.

The City of New Orleans Department of Safety and Permits (DSP) has developed and implemented a regulatory regime that has been internationally cited as a model for balancing the inescapability of this use with the protection of neighborhoods and residents. Over the course of several years, through formal planning studies, zoning ordinance text amendments, and prolonged negotiations with listing platforms, residents, interest groups, and neighborhoods, the city developed a robust package of practical and enforceable regulations that provided the market flexibility required by private industry.

This *PAS Memo* provides a case study of New Orleans's experience with this phenomenon and offers strategies and lessons learned for planners as they navigate this highly contentious issue.

Background and History of Short-Term Rental Regulations in New Orleans

New Orleans's history with transient rentals begins far before the age of digital bookings and informs the conversations of the last several years. In the 1960s, the Vieux Carré, or French

Figure 1. New Orleans's Vieux Carré (French Quarter). Flickr photo by Pedro Szekely (CC BY-SA 2.0).

Quarter, the oldest residential neighborhood in the city (Figure 1), was losing its inhabitants at an unsustainable pace. Hotel and tourism-supportive development were destroying the historic buildings that made the area attractive to tourists and pricing out the residents, businesses, and artists that created the unique nature of the neighborhood.

In 1969, a New Orleans City Council moratorium on hotel or transient lodging development in the Vieux Carré stemmed the tidal wave of hotel development and stabilized an otherwise at-risk community. This moratorium was converted to a permanent prohibition on hotel development through subsequent zoning changes. Even today the basis for opposition to tourist lodging in the Vieux Carré is still the nearly 50-year-old moratorium.

Early Attempts to Regulate Short-Term Rentals

As the nature of tourism changed through the years, residents began renting out homes or apartments during major festivals, such as Mardi Gras or the Jazz and Heritage Festival. New Orleans, as a major tourism destination hosting large-scale events on an annual basis, became a laboratory of creative ways to rent property.

The practice benefitted both parties to the transaction. New Orleans residents could vacation out of town during periods of high tourist volume when many businesses temporarily close or become overwhelmed. Visitors had access to a new pool of accommodations that could host families or groups too large to share a single hotel room or afford a traditional hotel.

This very capitalistic pairing of supply and demand naturally coalesced into a local cottage industry with unintended—but certainly not unforeseen—consequences. Over time, local property owners and outside investors noticed the demand for non-hotel accommodations and began acquiring property for the sole purpose of renting to tourists. This began displacing local residents, turning once-thriving neighborhoods into seasonal entertainment venues.

To address this burgeoning concern, the New Orleans City Council adopted Ordinance 21606 M.C.S. in 2004. This strong attempt by the city council to rein in vacation rentals ordained that:

> [i]t shall be unlawful for any person to knowingly offer to rent for monetary compensation for a period of less than 30 days or, in the case of premises located in the Vieux Carré District, 60 days, any living accommodations in the city if the premises offered for rent are not lawfully licensed or permitted for such use. (§54-491.1(b))

Should a property owner or lessor be prosecuted for the offense, the publication of such an offer to rent in print or electronic media would "create a rebuttable presumption that the person had knowledge of the offer to rent" (§54-491.1(d)).

At the time, the city's comprehensive zoning ordinance contained a defined use category of "Transient Vacation Rental" that provided three primary criteria in the classification of the use:

- the property was successfully rented for periods of less than 30 days (not just advertised as such)
- the property was rented to "non-residents"
- these rentals occurred over the course of a year or longer

Transient Vacation Rentals were allowed only within the Central Business District zoning districts, not any residential or business districts.

Unfortunately, however, the construction of these laws made enforcement virtually impossible, which led to growing frustration among neighbors who believed that the city was unwilling to enforce its own regulations regarding these uses.

The language of the 2004 ordinance outlawed only the "offer to rent" a living accommodation—it did not prohibit the action of executing such a rental. Additionally, the restriction was housed within the city's criminal code, which meant that any citation for the misdemeanor would have to be issued by the police department and the violation adjudicated by a judge in the city's municipal court. A second concern was the potential for a constitutional claim that the city was violating the free speech rights of property owners, because the restricted speech was not advertising a service prohibited by law.

DSP had administrative jurisdiction over the Transient Vacation Rental zoning provisions, but as noted above, the city was required to prove that rental actions of less than 30 days had physically occurred over a period of one year or longer.

Even with these limitations, in 2015 DSP chose to bring nine properties known to be in violation through its administrative adjudication process. Success would establish that DSP could build a prosecutable case under existing law where suitable documentation for violations existed and take actions against the hundreds of properties that had received complaints. However, if after years of compiling evidence, building cases, and partnering with neighbors to collect evidence the city was judged unable to meet its burden of proof in the administrative hearings, the cases would be dismissed.

A primary element of DSP's cases was the user reviews publicly available on websites such as airbnb.com. By matching neighbor complaints and documentation against the dates provided in the published reviews, DSP was confident in its ability to adequately meet the three-pronged burden of proof for operation of a Transient Vacation Rental. Recognizing the limitations of this body of evidence, DSP concentrated its efforts on the most egregious violators for which there was significant documentation.

But the adjudication hearings were never held. Days before the scheduled hearing, one of the property owners filed for a temporary restraining order against further proceedings due to vagueness of the charges and a constitutional challenge to the city's administrative hearings process. After several weeks of correspondence with the plaintiff's attorney, the city agreed to suspend prosecution of the nine cases. This agreement marked the end of active enforcement efforts against alleged STRs pending a new body of law.

Developing the New Regulatory Regime

The need for an updated regulatory package was now clear. Beginning in late 2014, a rough framework of reform began to take shape. If transient vacation rentals were legalized, the regulation process would have to be understandable and transparent to inspire confidence in the community. From these guiding principles, DSP, in coordination with the City Planning Commission and community stakeholders, began to formulate a new approach to regulation.

Whatever framework emerged had to be easily enforceable with a readily demonstrable burden of proof. But before the city could create a solution, it had to understand the problem.

The Short-Term Rental Study

In response to the now-demonstrated inability of the city to administratively enforce its transient vacation rental regulatory structure, in August 2015 the New Orleans City Council directed the City Planning Commission to study the regulation of these uses.

Over the course of nearly six months, the commission solicited information from neighborhoods, industry groups, hosting platforms, peer cities, and other agencies within the city to gain a full understanding of the nature of STRs as a land use—from the regulatory issues faced by DSP, to perception and documentable issues from neighborhoods, to the projected benefits of legitimizing the use fostered by the hosting platforms. Staff held more than a dozen meetings and multiple public hearings, and over 400 written comments were submitted to the commission (Rivers 2017).

In addition to these outreach efforts, the commission embarked on a study of documentable evidence and national best practices. In evaluating the practices of cities throughout the United States to determine previous regulatory successes and failures, the study found several key points (New Orleans City Planning Commission 2016):

- these uses fall into different categories and should be regulated differently based on location and rental type
- there must be performance standards to which operators can be held responsible to ensure the stability of neighborhoods
- fees and fines must be set at the appropriate level to encourage compliance while being impactful enough to penalize illegal behavior

Based on this study, staff presented four use types to the commission for consideration before a recommendation was made to the City Council: accessory, temporary, principal residential, and commercial (Figure 2). The commission voted to remove the "principal residential" type on the concern that this would cause exactly the scenario community groups feared most—turning residences into hotels and displacing residents.

In consultation with DSP, commission staff also recommended a series of requirements and performance standards creating an easily enforceable, comprehensive list of guidelines to ensure neighborhood compatibility, guest safety, and meaningful regulatory enforcement. These standards also provided many requirements with a low burden of proof for administrative enforcement, considered key to a high rate of compliance with the new regime.

Negotiation and Policy Priorities

The city knew that not gaining buy-in from the listing platforms would be a recipe for failure. Throughout policy negotiations, only Airbnb actively engaged with the process, which created the unintended result that compliance was easier for its platform than others. However, the city would work with other platforms following launch to bring compliance as close as possible in consideration of demonstrated technical and data considerations.

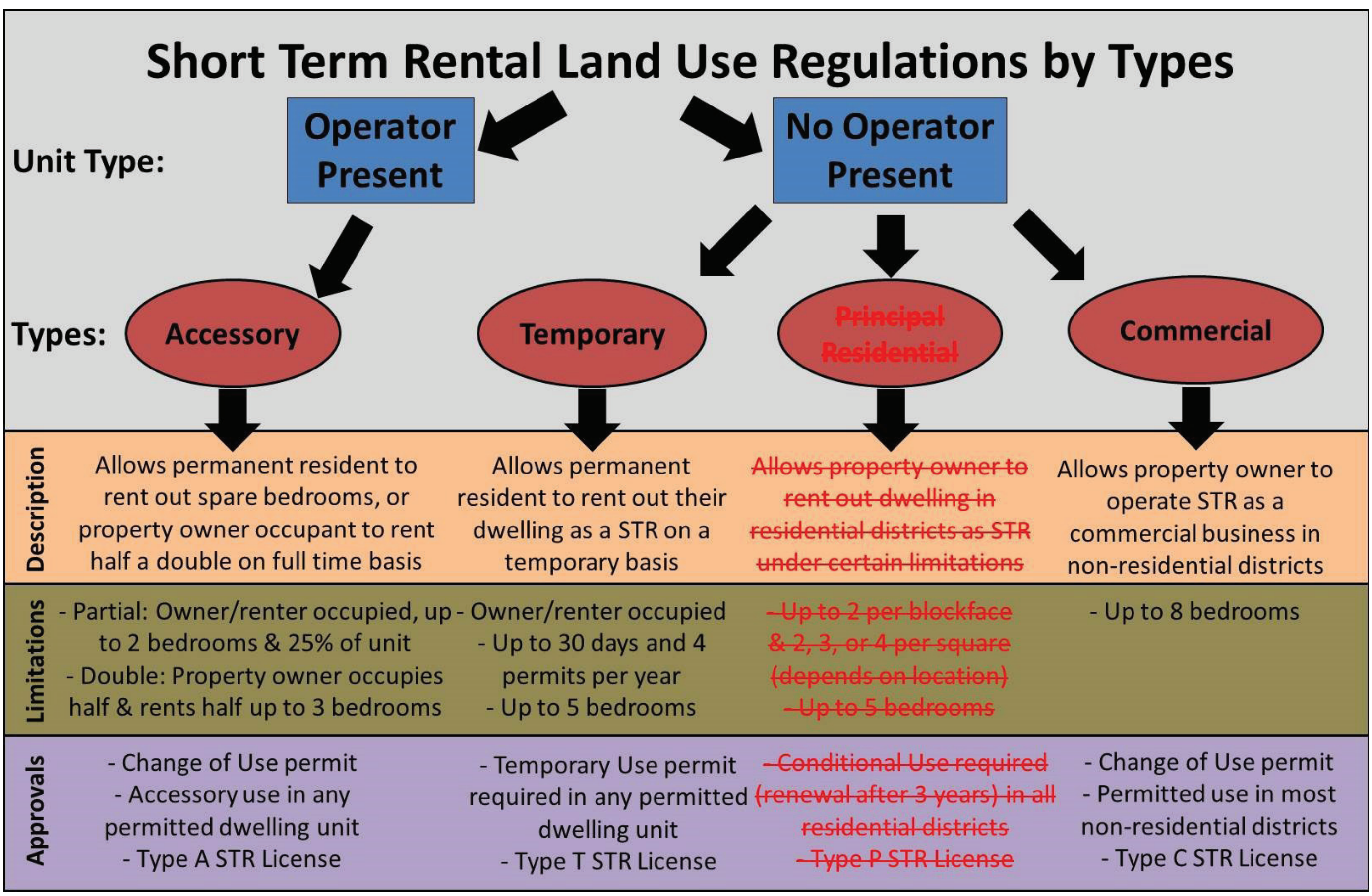

Figure 2. Short-Term Rental Types. Courtesy New Orleans City Planning Commission.

The New Regulations

The four ordinances adopted by the New Orleans City Council in 2016 established the provisions in the city code and zoning ordinance required to successfully implement the recommendations of the City Planning Commission's study and regulate STRs in New Orleans. Ordinances 27209 and 27204 provided the framework of the enforcement regime, including easily enforceable standards to allow swift citations of property owners who did not comply with the regulations. The other two ordinances addressed taxation and investment into the city's Housing Improvement Fund as mechanisms to turn STRs into a benefit to the communities they would be occupying.

Ordinance 27204 M.C.S. This ordinance (codified as §26-613 et seq.) established a licensing and enforcement regime, provided for a public registry of licensed STRs as well as provisions for datasharing with the listing platforms, and set fees and penalties for the program. The licensing provisions formally created three license types (accessory, temporary, and commercial) corresponding to concurrently created zoning land-use types, and provided safety and compliance standards by which DSP would evaluate applications for these licenses. To maintain a low barrier to entry into the permitting process, applicants were permitted to comply with these provisions by attestation, with DSP following up to verify compliance. Falsification or misrepresentation of any material information in the application process would result in the immediate revocation of the license.

Ordinance 27209 M.C.S. This zoning text amendment ordinance implemented the changes outlined in the city planning commission's 2016 study. It defined the STR land use generally, as well as the specific STR subcategories (accessory, temporary, and commercial), and imposed standards and requirements for the three use types. Additionally, this ordinance amended the permitted use tables to designate where STRs would be permitted as by-right or conditional uses. Accessory STRs were permitted within any legal dwelling unit located within an owner-occupied single- or two-family dwelling (except for within the Vieux Carré). Temporary STRs would be permitted in any legal dwelling unit (except within the Vieux Carré) without consideration of owner occupancy but with a 90-night occupancy limitation. Commercial STRs would be permitted in virtually every commercial zoning district, including the Vieux Carré Entertainment District (Bourbon Street) but excluding the remainder of that neighborhood.

The standards can be broken into two primary categories (see table below). Regulatory compliance standards are black-and-white requirements for which the city can easily demonstrate noncompliance, while performance compliance standards are more subjective in nature and require a higher level of documentation to determine noncompliance.

Regulatory Compliance	Performance Compliance
• All short-term rentals require a license. • License placard to be prominently displayed in a manner visible from the public right-of-way. • License number to be posted on any rental listing. • Any rental listing must match the occupancy limitations of the approved license. • Any short-term rental has to have the outward appearance of a residential building. • Short-term rentals may not occupy any accessory structure, outdoor space, or recreational vehicle.	• Only one party of guests is allowed in a short-term rental unit. • The number of guests may not exceed occupancy limitations stated on the license. • An in-town contact must be available to address any unruly guests or dangerous situations. • The rental shall not adversely affect the residential character of the neighborhood. • The rental shall not generate noise, vibration, odors, or other effects that unreasonably interfere with any person's enjoyment of their residence.

Ordinance 27210 M.C.S. This ordinance imposed a $1.00-per-night fee on STRs above the city's standard tax structure directed to the Neighborhood Housing Improvement Fund, a limited-access fund that can be used only for community development under specific guidelines.

Ordinance 27218 M.C.S. This ordinance authorized the mayor to enter into a cooperative endeavor agreement with Airbnb, which agreed to collect and remit taxes on behalf of its users by including the required taxes and fees at the time of booking. This saved the city from creating tax accounts for every licensed property and requiring property owners to calculate and remit taxes individually. This was part of the negotiation process with the listing platform that would ease the regulatory burden on both the city and licensees—creating a "win" on both sides of the taxation transaction.

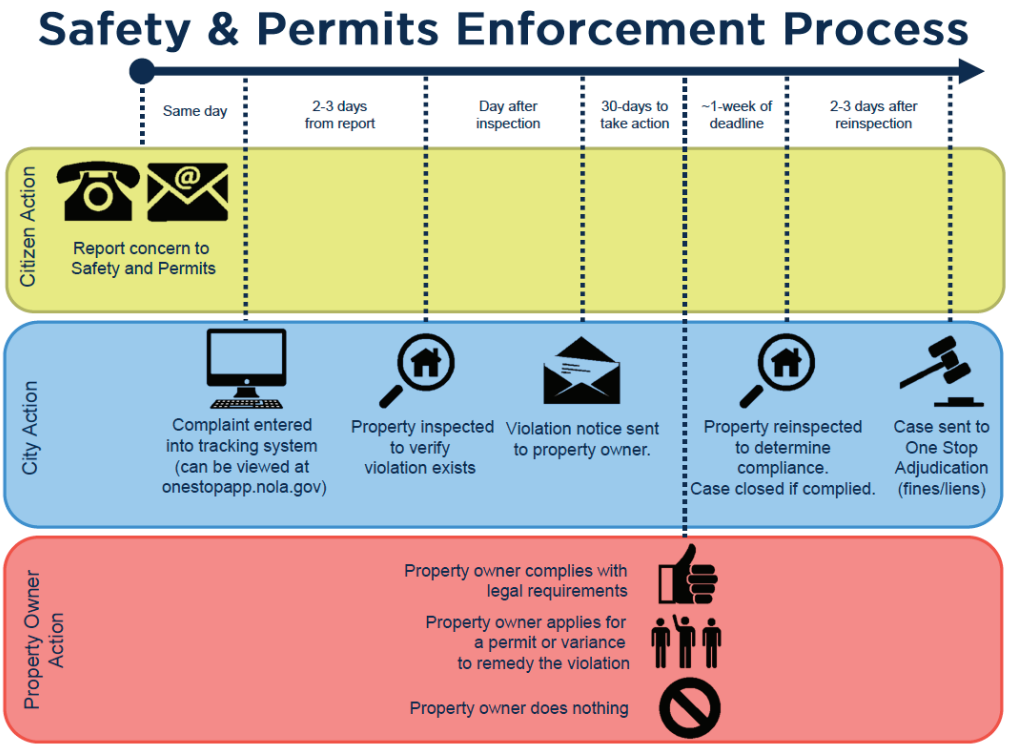

Figure 3. DSP's short-term rental enforcement process. Courtesy City of New Orleans Department of Safety and Permits.

Negotiations at this phase also took place with community leaders, city council members, and interest groups to create a structure that would be acceptable to the majority of stakeholders. Key points were appropriate annual limitations on temporary rentals, the mechanics and scope of data sharing, and the level of control platforms would have over encouraging compliance among their users.

Annual limitations on rental nights was one of the most public points of debate as the legislative process drew to a close. Type A (accessory) and Type C (commercial) licenses would have no limitations on annual rentals, but Type T (temporary) licenses would be subject to an annual cap on the number of nights the property could be rented out. STR advocates pushed for periods as long as 180 nights, while opponents, short of a ban, believed that the spirit of a "temporary" license could be satisfied with a cap of 30 nights per year (which was also the position of the commission). The city council ultimately decided to allow Type T rentals across the city with a maximum annual rental of 90 nights.

The remaining two points of negotiation, data sharing and platform assistance in overall compliance, were resolved as two sides of the same coin. The city would require data on rentals to enforce the 90-night cap on Type T licenses, and the listing platforms agreed that assistance from their side would boost user compliance with the new regulations and provide better data to track rentals, while the new standards would help ensure the safety of guests.

As part of the overall agreement, the platforms would voluntarily remove any unlicensed listings from their platform after a reasonable compliance period. The city would coordinate a pass-through registration program that would allow applications to be filed through Airbnb's website, then uploaded into the city's permitting and licensing database. Additionally, Airbnb agreed to share certain anonymized data each month: a unique identifier for each listing, the number of nights rented in the last 30 days, and the total nights rented year-to-date. If additional information was required, the platform agreed to an administrative subpoena process, all of which was codified as Section 26-620 of the New Orleans City Code.

Implementation and Enforcement of STR Regulations

On December 1, 2016, the New Orleans City Council adopted four ordinances to implement the new STR program. The ordinances provided for regulation and taxation of STRs, as well as other administrative functions that aided the process (see sidebar).

As a result of the legislative action, DSP created the Short Term Rental Administration to serve as the single point of contact for the public in the licensing and enforcement process. Without this administrative office, the authority of implementation and enforcement would have been spread across several administrative units within DSP.

Building Public Confidence

As the agency responsible for licensing and enforcement, DSP knew that public confidence from day one would be critical for success. To demonstrate the city's intention of complete transparency and full compliance, the website nola.gov/str was launched on December 2, 2016, with all available information on the program: the data available from the 2016 study, the subsequent ordinance adoption process, and approximate timelines for program benchmarks.

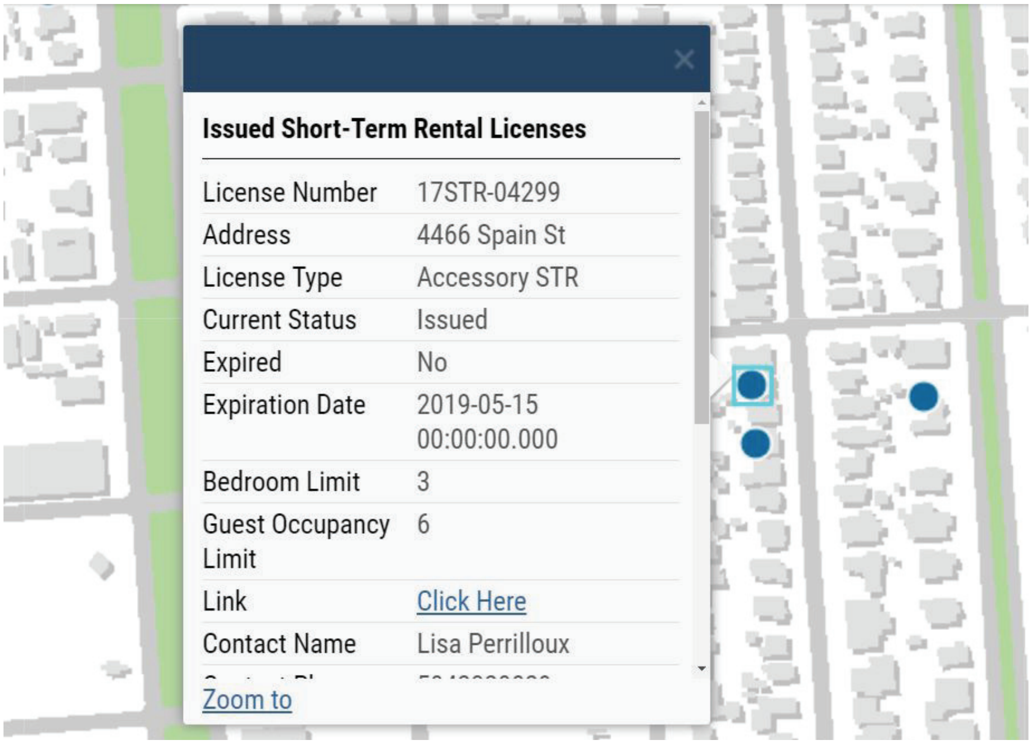

Figure 4. The city's interactive short-term rental registry and map. Courtesy City of New Orleans Department of Safety and Permits.

Within days, staff updated this website with information distilled from the adopted ordinances, simplifying the requirements and creating tables to help users understand the zoning restrictions. There were four months from adoption to the April 1, 2017, effective date to create internal and external processes for something that had never been tried before. DSP would focus its attention on three areas during this period: development of a robust internal process, transparency in process and enforcement, and development of a strong enforcement presence.

Development of Internal Processes

Internal processes were the first focus. Database configuration started early in the legislative process, which then allowed DSP to focus on other areas of internal process standardization: the pass-through connection from the city's database to Airbnb, a comprehensive analysis of license application workflow, and development of the enforcement regime that would be implemented.

Ultimately, the pass-through process was not a panacea of compliance as many hoped. Staff required information for license processing beyond that needed by the listing platform, so separate correspondence with every applicant was still required, and every applicant had to return to the city's permitting and licensing portal (onestopapp.nola.gov) to pay for the license prior to issuance.

A license application workflow needed to be developed and standardized. The expectation of a same-day turnaround, paired with the need to streamline the process to the furthest extent possible for pass-through integration, led DSP to reimagine a number of internal processes and ways staff could be cross-trained to address peak workloads. Printed and digital forms had to balance information that the average applicant would have available against whether the city was capturing all necessary data in the license review process.

This same level of creativity became necessary in developing enforcement protocols. The new regulations required a methodology for how staff would collect data, record violations, and build cases (Figure 3, p. 5). DSP could then use that standardization to set community expectations for enforcement action.

Transparency in Process and Enforcement

The commitment to providing all available information to the public in an easily digestible format remained the policy of DSP. A public-facing portal for its permitting and licensing database (onestopapp.nola.gov) that allows users to search for activity on a given property in real time was made easily searchable for STR license approvals or enforcement cases.

The ordinances took transparency one step farther in requiring publication of a list of all STR licenses, along with the property address, license holder name, and the contact information for the responsible party. This allows a neighbor to contact someone about a problem with a rental. To fulfill this requirement, DSP coordinated with the city's Office of Information Technology to develop an interactive STR registry and map. This tool allows users not only to search by name or property address, but also to see all license applications on a map of the city (Figure 4).

During this time, DSP leadership participated in numerous neighborhood meetings to outline the process, regulations, guidelines, and enforcement strategies. The focus was on implementing a program that would succeed and deliver on the promise that was made to the council and, more importantly, the community.

City of New Orleans
Department of Safety & Permits
Short Term Rental Administration

Field Warning

Location: ____

Date: _________________ Time: ______________

This notification is intended to inform the owner/operator of this premises of failure to comply with the City's Short Term Rental requirements. Legislation and information on Short Term Rentals in New Orleans is available at www.nola.gov/str

- ☐ This property has been reported as an operating short term rental, but our records indicate no application on file.
- ☐ This property is registered as a licensed short term rental, but no license is posted.
- ☐ This property is licensed as a Short Term Rental, but we have received a complaint of excessive:
  - ☐ Noise
  - ☐ Vibration
  - ☐ Glare
  - ☐ Odors
  - ☐ Other effects

  Which unreasonably interferes with neighbors enjoyment of their residence.
- ☐ This property is registered as a licensed short term rental, and there have been reports of unpermitted commercial or social events that may result in license revocation.
- ☐ This property has a license posted, but our records indicate that the license was issued for a different location/address.
- ☐ This property has been reported as an operating short term rental, but is located in a portion of the French Quarter where Short Term Rentals are prohibited.

Please contact the Short Term Rental Administration at 504-658-7144 or str@nola.gov for additional information. A formal violation letter will also be mailed to the owner of record within the week to initiate adjudication procedures.

City of New Orleans
Department of Safety & Permits
Short Term Rental Administration

Figure 5. Field warning tags to flag short-term rental noncompliance. Courtesy City of New Orleans Department of Safety and Permits.

Importance of a Strong Enforcement Presence

DSP needed to assure doubtful residents that enforcement would be both proactive and responsive. To that end, the agency took two new simple, cost-effective actions.

First, DSP developed "field warning" tags to post on STR properties where a violation was believed to have occurred (Figure 5). These were simple half-sheet forms with checkboxes for common violation types, allowing an inspector to post a notice to the property owner on the spot and document the posting via photograph. But most importantly, these documents are hot pink and unmistakable as a "scarlet letter" of STR noncompliance to show neighbors that inspectors were on the job.

The second action was to brand DSP's vehicles as such. Prior to 2017, all DSP vehicles were tagged as city vehicles, but these markings did not indicate to which department the vehicle belonged. Residents wanted DSP to work into the evenings and late at night during major events to maintain compliance with the STR performance standards provided in the city code. Based on these community concerns, vehicles were branded as "Department of Safety & Permits" to provide a level of visibility critical to maintaining the confidence of neighbors in the overall regulatory regime.

One last key element of the city's STR regulations is based on a long-standing provision of the building code that authorizes termination of utility services if a property is found to be in violation of the zoning ordinance. To eliminate any potential challenge to the use of these provisions, the enabling legislation for the licensing regime explicitly states that discontinuance of electrical service is an appropriate penalty for violation of the licensing provisions (§26-618).

Within four months of program launch, the Short Term Rental Administration sought its first utility disconnect order against a property owner in the Vieux Carré who would not remove online listings or stop using the property as a STR. The city's utility provider terminated electrical service to the dwelling, and from that point compliance was swift and the property was soon sold.

Status of STR Administration After Year One

The STR program in New Orleans celebrated its first anniversary on April 1, 2018, and DSP is proud of the success achieved in the implementation of the program.

In the first 12 months, the Short Term Rental Administration reviewed more than 8,000 applications and issued 4,477 licenses (Figure 6). This generated $979,274 in permit fees, exceeding expectations and completely covering the administrative costs of the program. Based on the 2016 study's estimate of 4,000–5,000 STRs operating in New Orleans and the number of licens-

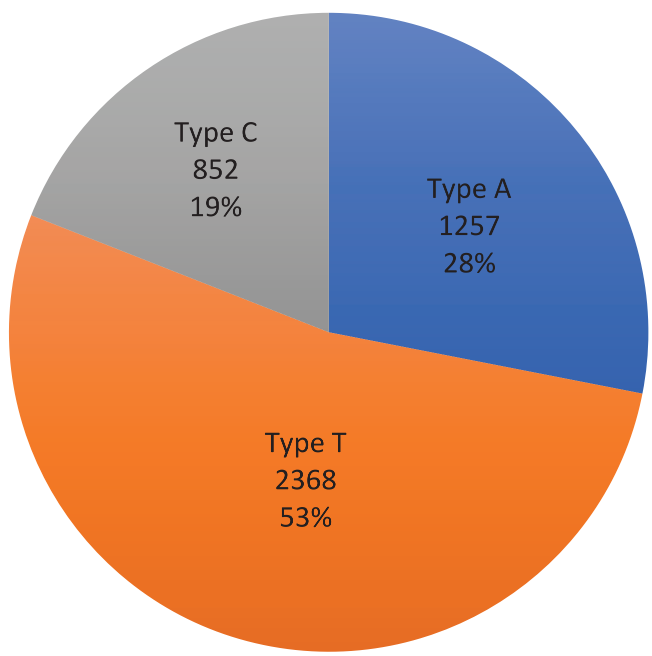

Figure 6. Breakdown of STR licenses by rental type. Courtesy City of New Orleans Department of Safety and Permits.

es issued during the first year of program implementation, DSP believes the compliance rate is in the high 90 percent range.

In terms of enforcement activities, DSP opened 1,719 violation cases between January 1, 2017, and April 1, 2018, from which 280 administrative hearings were held and $268,538 in total fines assessed.

The mechanisms for identifying and enforcing rentals in prohibited zones and licensing requirements were successful, but challenges remained. Type T rentals made up the largest share of licenses issued, but also proved to be the most problematic from both a regulatory and neighborhood perspective. This became the single largest liability to the program.

Key to administering the Type T license was the ability of the city to monitor and enforce compliance on the 90-night annual rental cap provided in the adopted regulations. While the listing platforms initially represented that they would be supportive of the licensing program and provide the necessary information to DSP, both Airbnb and HomeAway subsequently declined to provide complete rental documentation based on their interpretation of the Stored Communications Act (see sidebar). As a result, while monthly reports could tell the enforcement team how many nights all STRs were rented, those numbers were not tied to specific properties or listings to allow meaningful, consistent enforcement action.

Because of the problems caused by the Type T STRs, the public was not completely satisfied with the initial iteration of the STR program. While the city was proud of the overall success rate in terms of registration and enforcement effectiveness, the inability to effectively police the annual rental cap led to a public pushback against elected officials who were viewed as being nonresponsive to this inability.

Implemented and Proposed Changes to the Program

The city's municipal elections were held in the fall of 2017, and STRs featured prominently in city council campaigns. Of the three district councilmembers running for reelection, the only one reelected was the sole councilmember to vote against the STR regulations. The new city council came into office with a clear intention of revisiting the regulatory regime.

During the transition period, then-Councilmember LaToya Cantrell (now mayor) initiated two separate actions that would lay the foundation for updating the city's STR regulations. The first was the proposal and ultimate adoption of a zoning text amendment to require conditional use approval for some STRs

The Stored Communications Act and Its Effect on STR Enforcement

As planners negotiate the regulatory and enforcement balance of STR program development, the city or county legal team should be consulted in the early stages of the process about the Stored Communications Act (SCA), an element of the Electronic Communications Privacy Act of 1986 intended to ensure the privacy of electronic records created by a company about its customers. If communities are developing local regulations reliant on data sharing by hosting platforms, they must be aware of the SCA and ensure the proper provisions are in place to minimize its impact on STR enforcement efforts.

New Orleans's data-sharing provision within the new licensing regime required routine reporting of basic rental information to help the city monitor compliance with the 90-night rental limitation for Type T rentals. Key to the effectiveness of this agreement was the provision for issuance of administrative subpoenas to get specific user data based on potential violations identified based on the anonymized data being provided on a monthly basis. While the hosting platforms suggested the administrative subpoena provisions during regulatory negotiation, once these subpoena were issued they became less-than-willing partners in providing the necessary data to match anonymized data to specific properties or licenses.

Under the SCA, platforms have to provide any requested data subject to either a subpoena issued by a court or an administrative subpoena authorized by federal or state statute. In the case of New Orleans, the subpoena authority under which DSP requested this information was the city's home rule charter, which is enabled by the Louisiana Constitution. However, the hosting platforms deemed this insufficient to turn over anything more than "basic subscriber information" as provided by the SCA and subsequent jurisprudence. (There is currently no legal consensus on how the SCA should be applied to listing platforms.)

The "basic subscriber information" provided illustrates how difficult Internet regulation can be, particularly for a local government. To fill in the gap between specific property and anonymized identification number, HomeAway and Airbnb provided the first and last name of the account holder and their user identification number, email address, and telephone number—but not the license number issued by the city associated with the listing or the property address. As a result, city staff needed to match names, email addresses, and telephone numbers with over 4,000 issued licenses. This highlighted one problem that DSP had not planned for: licenses issued to property owners but listings posted or managed by a third party.

In revisiting the 2016 regulatory structure, deficiency in data production was one of the primary concerns. Had the city been aware of the industry's use of the SCA as a shield against providing the information required to properly implement and enforce the proposed program, the regulations as initially adopted would have likely looked quite a bit different. This would have likely ranged from creating a licensee-reporting requirement to elimination of the Type T license entirely. What is certain is that the changes being evaluated by the city planning commission and the city council in 2018 are keeping the SCA in the forefront as they evaluate how best to modify the STR licensing regime to ensure compliance and enforceability.

in the city's historic urban core business districts. This change was made in response to the concerns of neighbors that structures containing apartments were being converted into "hotels" in otherwise neighborhood-scale commercial corridors. The second action directed the City Planning Commission to conduct a full study of the new STR regulatory regime.

When the new city council took office in May 2018, it wasted no time in delivering on the promises made to its constituents. At the second meeting of the new term, the council adopted Motion M-18-195: a partial moratorium on new STR licenses with a full prohibition on Type T STR licenses in the historic areas of the city, the central business district, and mixed use districts, and a prohibition of new Type C STR licenses on the first floor of mixed use buildings, though they would remain permitted on upper floors. This moratorium was scheduled to last nine months while the commission completed its study and the city's regulations were updated.

The commission completed its updated study in early October 2018 (New Orleans City Planning Commission 2018). While the study makes several recommendations, the most substantial is the elimination of the problematic Type T STRs. Type C STRs would carry on, but the Type A STRs would be redefined to cover nearly any owner-occupied property. A new third type of license, valid for special events only, would allow owners or rental tenants to rent out a permanently occupied dwelling unit for not more than 14 days per year. At the time of writing, the city council has not yet taken action on the report, but it is likely that that will do so within the next several months.

Lessons Learned

STRs are a planning challenge: they are residential units by design but can act like hotels in their impact on a community. A proliferation of these uses—particularly in tourism-heavy cities—can lead to significantly increased housing costs and begin to price out actual residents in favor of residents for-a-day. New Orleans's experience in studying and regulating STRs highlights several key considerations in dealing with this issue.

Ensure that regulations are clear and enforceable. In developing the STR regulations, planning staff worked closely with DSP to ensure that enforcement was based on the information likely to be available. Compliance is easily provable for regulations such as requiring a license and requiring that license to be posted. Some STR regulations lie in more of a gray area, such as nuisance prohibitions, but with rigid enforcement standards and vigilant neighbors these have also proved enforceable.

Partner with listing platforms when possible. Partnerships can either be formal or informal, but platform buy-in helps ensure consistent communication on regulatory requirements and may aid in enforcement. The city's data-sharing agreement with Airbnb allowed DSP to coordinate actions to de-list unlicensed properties posting on that platform. While this was not a complete solution to illegal rentals, it greatly improved compliance rates throughout the city and helped stop rental listings in the Vieux Carré.

Recognize your limitations. Initially, residents and councilmembers pushed to regulate STR listing platforms in the same way that DSP regulates transportation network companies (TNCs). Where the city has the authority to regulate TNCs due to the long-standing regulation of vehicles-for-hire, that level of regulatory authority was not possible for dwellings, where state law prohibits local governments from regulating contractual transactions relative to real property. To address this lack of direct regulatory authority, the city negotiated data sharing to the extent possible and crafted regulations that could withstand legal scrutiny.

Coordinate STR policy making with policies surrounding affordable housing. While New Orleans began to take this approach by requiring contributions to the City's Neighborhood Housing Improvement Fund, there was no consistent strategy for the investment of those fees. A combination of this and the proliferation of Type T STRs had the effect of pricing out long-time residents and artificially inflating property values due to the expectation of return on investment.

Conclusion

During 2017, the City of New Orleans became a model for STR regulatory compliance across the nation. Thanks to data sharing and some regulatory assistance from Airbnb, DSP was able to successfully license nearly 5,000 short-term rentals. This represents a compliance rate above 90 percent in less than one year, while many peer cities struggle to reach a 20 percent compliance rate after one year.

While the city was proud of this achievement, it understood that the regulatory regime would need to be revisited after the first year to evaluate neighborhood impacts and overall compliance—and indeed, regulatory enforcement proved more difficult, especially for the Type T temporary STR licenses. The city hopes to resume enforcement of licensing standards in cooperation with listing platforms as this regulatory revision comes to a close.

Just as New Orleans is now revisiting the initial regulatory structure to respond to changing dynamics of the industry and public sentiments, planners will need to be prepared to continually address issues like STRs for years to come. There is no formula which can be applied across every jurisdiction to address the impacts of the use and the concerns of residents. Rather, it is our job to understand the implications of decision making, continually observe the effects of those decisions, and recommend change when necessary—recognizing that maybe we were wrong the first time.

Regulation of emerging technologies is not new to planners, and STRs will not be the last challenge of this sort we face as practitioners. Combining best practices and lessons learned in New Orleans can help communities across the country develop and implement regulatory structures that will adapt to emerging technologies and industries while also protecting residents and the stability of communities.

About the Author

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vember 2012 through June 2018 and worked closely with the City Planning Commission, City Council, and the Landrieu and Cantrell administrations in shaping the regulatory and enforcement processes of the New Orleans Short Term Rental Program. Munster holds an undergraduate degree in urban studies and planning, a master's degree in urban and regional planning, and a PhD in urban studies from the University of New Orleans. He is also a certified floodplain manager and is presently serving as the interim executive director of the Regional Transit Authority of New Orleans.

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