# The Welfare Effects of Peer Entry in the Accommodation Market: The Case of Airbnb[1]

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**Abstract**

We study the entry of Airbnb into the accommodation industry and its effects on travelers, hosts, and hotels. We first document heterogeneity in Airbnb's penetration across 50 major US cities and demonstrate that much of this heterogeneity can be explained by proxies for hotel costs, the costs of peer hosts, and demand fluctuations. Next, we document that Airbnb has an effect on hotel revenues. This effect is mostly due to a reduction in hotel prices rather than occupancy and is greatest in cities with low hotel capacity relative to the size of demand. Finally, we estimate a structural model of competition between peer hosts and hotels and use it to study the effects of Airbnb on the distribution of surplus across consumers, peer hosts, and incumbent hotels. We find an average consumer surplus of $70 per night from Airbnb. This surplus is disproportionately concentrated in locations (New York) and times (New Year's Eve) when hotels have high occupancy. Because Airbnb guests view Airbnb as a differentiated product and because Airbnb bookings occur disproportionately when hotels are near full capacity, most of these bookings would not have resulted in hotel bookings had Airbnb not been available. We also quantify the effects on hotels

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and peer hosts. In total, the sum of the surplus from Airbnb entry across consumers, hotels, and hosts is $352 million in 2014 for the top 10 US cities in terms of Airbnb's penetration.

# 1 Introduction

The Internet and related technologies have greatly reduced entry and advertising costs across a variety of industries. As an example, peer-to-peer marketplaces such as Airbnb, Uber, and Etsy to provide a platform for small and part-time service providers (peers) to participate in economic exchange. Several of these marketplaces have grown quickly and have become widely known brands. In this paper, we study the determinants and effects of peer production in the market for short-term accommodation, where Airbnb is the main peer-to-peer platform and hotels are incumbent suppliers. Specifically, we present a theoretical model of peer competition with traditional firms and use the example of Airbnb to estimate the model and quantify the effects of Airbnb on consumers, hotels, and Airbnb hosts.

Since its founding in 2008, Airbnb has grown to list more rooms than any hotel group in the world. Yet Airbnb's growth across cities and over time has been heterogeneous, with supply shares ranging from over 15% to less than 1% across major US cities at the end of 2014. We propose a theoretical framework based on economic fundamentals to explain this heterogeneity. In our framework, accommodations can be provided by either dedicated or flexible supply – hotels vs peer hosts. The main difference between dedicated and flexible producers is that dedicated producers have higher investment costs while flexible sellers typically have higher marginal costs.

The role of Airbnb in our framework is to lower entry costs for flexible producers. This reduction in entry costs is similar across geographies but the benefits of renting accommodations vary. In the long-run, the entry of flexible producers is driven by the trend and variability of demand in a given city, hotel investment costs, and peer rental costs. We confirm that these predictions hold in our data.

In the short-run, flexible producers decide whether to host on a particular day. Because of the flexible nature of their supply, we hypothesize that these producers will be highly responsive to market conditions, hosting travelers when prices are high, and using accommodation for private use when prices are low. In contrast, because hotels have only rooms dedicated to travelers' accommodation, they will typically choose to transact even when demand is relatively low. We validate this prediction by documenting that the elasticity of supply is 92% higher for flexible producers than for hotels.

Next, we estimate a model of short-run equilibrium and use it to quantify the effect of Airbnb on total welfare and its distribution across travelers, peer hosts, and hotels. Travelers benefit from Airbnb for two reasons. First, flexible sellers offer a differentiated product relative to hotels. Second, they also compete with hotels by expanding the number of rooms available. This second effect is particularly important in periods of high demand when hotels are capacity constrained and have high market power. Consequently, we find that the consumer surplus is concentrated in cities where hotel expansion is restricted and in periods of high demand. In those cities and periods, flexible sellers allow more travelers to stay in a city without greatly affecting the number of travelers staying at hotels.

We enumerate our main quantitative results below, where the sample consists of the ten largest cities in terms of Airbnb share in the US for 2014. First, consumer surplus per night booked on Airbnb is \$70, and 71% of this surplus comes from the fact that Airbnb listings are preferred to hotels by a share of consumers at prevailing prices. The rest of the surplus is due to Airbnb's negative effect on hotel prices. This effect is largest when hotels have market power due to being at or near full capacity. The total consumer surplus gain from Airbnb is \$432 million, with the largest gains coming in New York City. Second, we find that over 70% of Airbnb bookings would not have been hotel stays had Airbnb not existed. Third, the entry of Airbnb results in a 1% loss in hotel revenues in this sample. Lastly, peers receive an average of \$28 in surplus per night, resulting in a host surplus of \$20 million in 2014.

Our data mainly comes from two sources: proprietary Airbnb data and Smith Travel Research (STR), a hotel industry data aggregator. For both datasets, we prices and occupancy rates at a city, day, and accommodation type level between 2011 and 2014 for the 50 largest US cities.[1] We use this data to document heterogeneity in the number of Airbnb listings across cities and over time. Cities like New York and Los Angeles have grown quickly in terms of available rooms on Airbnb, while cities like Oklahoma City and Memphis have grown at lower rates. Within each city over time, the number of available rooms is higher during peak travel times such as Christmas and the summer. The geographic and time heterogeneity suggests that hosts flexibly choose when to list their rooms for rent on Airbnb, and are more likely to do so in cities and times when the returns to hosting are highest.

In section 2, we incorporate this intuition into a model of the market for accommodations. In this model, hosting services can be provided by dedicated or flexible sellers, and products are differentiated. Dedicated sellers are characterized by high investments costs, but low marginal costs. Since dedicated capacity is always available to travelers and has no alternative use, investment in dedicated capacity is justified when rooms are frequently occupied. Instead, flexible capacity does not require any investment but typically involves higher marginal costs to operate. On Airbnb, hosts do not always have a room available for rent, and when they do, they must prepare the room and interact with the guests before and during the trip. Hosting is also perceived as risky by some individuals.

Our model includes two time-horizons. The long-run horizon is characterized by the entry

[1]The 50 largest US cities were selected on the basis of their total number of hotel rooms.

decision of flexible sellers given the new Airbnb platform. The short-run horizon focuses on daily prices and quantities of rooms rented, taking flexible and dedicated capacity as given. We model the decision of flexible sellers to join the platform as dependent on the expected returns from hosting, which depends in turn on competition from hotels and overall demand. We define the short-run horizon as one day in one city. In the short-run, the capacity of flexible and dedicated sellers is fixed. Travelers choose an accommodation option among differentiated products, e.g. luxury vs economy hotels, and hotels vs Airbnb rooms. The demand for these goods varies over time due to market-wide demand fluctuations, such as seasonality, and idiosyncratic product-specific demand shocks (e.g. Berry et al. (1995)). On the supply side, hotels compete in a Cournot game with differentiated products subject to capacity constraints and with a competitive fringe of Airbnb hosts. Hosts take prices as given and host travelers if the market clearing price on the platform is greater than their cost of hosting.

The model offers testable predictions. The long-run share of flexible sellers should differ across cities. Entry should be largest in cities where hotel investment costs are high, flexible sellers' marginal costs are low, and demand variability is high so that there are periods of high prices. In the short-run, flexible sellers should increase competition: they will reduce prices and occupancy rates of hotels, and the effects will be largest in cities where hotel capacity is low relative to demand. We describe those cities as having constrained hotel capacity. In those cities, the model predicts that Airbnb reduces prices more than occupancy rates.

In section 3, we confirm that these model predictions hold in the data. We first look at the long-run patterns. We show that peer supply as a share of total supply is larger in cities where hotel prices are higher. These high prices are associated with the difficulty of building hotels due to regulatory or geographic constraints. Peer supply is also larger in cities where residents tend to be single and have no children. These residents likely have lower costs of hosting strangers in their homes. Another factor influencing peer supply is the volatility of demand. A city can experience periods of high and low demand due to seasonality, festivals, or sporting events. When the difference in peaks and troughs is large, the provision of accommodation exclusively by hotels can be inefficiently low. We show that Airbnb's supply share is larger precisely in cities with high demand volatility, and, perhaps more intuitively, in cities where demand growth is high.

We then test the predictions of the model on short-run hotel outcomes. We do this by estimating regressions of hotel outcomes on a measure of Airbnb supply using two types of instruments as well as controls for aggregate demand shocks. Measurement and endogeneity challenges are discussed in subsection 3.2. On average, a 10% increase in the number of available listings on Airbnb reduces hotel revenues by 0.36%. This effect is mostly due to a reduction in hotel prices rather than a decrease in occupancy rates and is heterogeneous across cities. The effect is larger in cities with constrained hotel capacity, where a 10% increase in Airbnb listings decreases hotel prices by 0.52%. In other cities, the reduction is quantitatively small and statistically insignificant. The heterogeneity in estimates is due to differences in both the size of Airbnb and the effects of Airbnb across markets conditional on that size. The magnitude of the reduced form coefficient and the finding of greater effects on pricing is broadly in line with the work of Zervas et al. (2015), who focus on the average effects of Airbnb on hotels in Texas.

In section 4, we describe our estimation strategy for recovering the primitives of the model from section 2. Our estimation strategy combines a random coefficient multinomial logit demand model (Berry et al. (1995)) with hotels' pricing decisions. In order to take into account the fact that prices steeply increase when occupancy reaches hotel capacity, we follow Ryan (2012) and rationalize these price changes with increasing marginal costs that operate when hotels are close to their capacity constraint. We also augment our estimation with survey data regarding the preferred second choices of Airbnb travelers. Finally, we estimate the marginal cost distribution of hosts on Airbnb assuming that they are price takers. Together, these estimates allow us to measure consumer and peer producer surplus, as well as to quantify how surplus would change in the absence of the Airbnb platform.

Section 5 presents our results. We find that consumers' utility for Airbnb is lower than for hotels, but that preferences for Airbnb increase between 2013 and 2014. By the end of the sample period, the mean utility from top quality Airbnb listings is close to the mean utility of economy and midscale hotels in cities with a large Airbnb presence. Consistent with our model, we find that flexible sellers have higher marginal costs than dedicated sellers on average, and that the distribution of peer costs makes flexible supply highly elastic.

In the absence of Airbnb, total welfare would be lower and travelers and peer producers would be worse off. However, hotels would gain from the reduced competition. We find that for New York, the city with the largest Airbnb supply in our sample, consumer surplus would be $207 million lower if Airbnb did not exist in 2014. This corresponds to a consumer surplus of $69 per night for every Airbnb booking in New York.

The reduction in consumer surplus if Airbnb did not exist occurs because fewer travelers would book rooms, and travelers who end up booking hotel rooms would pay higher prices. As it turns out, because of the elastic supply of Airbnb rooms, actual Airbnb bookings, and hence surplus gains, disproportionately occur in cities (New York) and times (New Year's Eve) when hotel capacity constraints bind. This implies that in the absence of Airbnb, travelers could not easily find a substitute hotel room because hotels would be fully booked. Indeed, we find that over half of Airbnb bookings would not have been hotel stays had

Airbnb not existed.

The concentration of Airbnb bookings in cities and periods of peak demand suggests that in the absence of Airbnb, hotels would be limited in their ability to increase the number of booked rooms – they are already operating at or close to full capacity – but instead would be able to increase prices. This is consistent with our reduced form evidence, and it is precisely what we see in our counterfactuals. Revenues for hotels in New York would increase by 1.5% if Airbnb did not exist and a measure of profits would increase by 3.05%.

The growth of peer production in the accommodations industry is important to study because of its business and regulatory implications. As Airbnb grows, other actors in the industry such as hotels, OTAs, and peer hosts must learn how to adopt. Second, many cities wish to regulate the peer producers in the accommodation industry but there has been much disagreement regarding the specific form of this regulation. If Airbnb only affected hotels, travelers, and peer hosts, then our results suggest that the net contribution of Airbnb is positive. However, there are potential effects on housing, labor markets, and the neighbors of hosts that we do not consider in this paper and leave for future research.

We contribute to the growing empirical literature on online peer-to-peer platforms. A limited number of papers have looked at the effect of online platforms on incumbents, in particular Zervas et al. (2015) for Airbnb, Seamans and Zhu (2014) and Kroft and Pope (2014) for Craigslist, and Aguiar and Waldfogel (2015) for Spotify. We estimate the effects not only on incumbent firms but also on consumers and new producers. Furthermore, we are able to document how these effects vary over time and across cities and conduct counterfactual simulations. Another complementary paper to ours is Cohen et al. (2016), which uses discontinuities in Uber's surge pricing policy to estimate the consumer surplus from ride sharing. Both of our papers find that successful peer-to-peer platforms generate substantial consumer surplus. However, the mechanisms which generate this surplus differ between our papers. While Cohen et al. (2016) assume that market structure remains constant, we incorporate capacity constraints and allow for hotel prices to adjust endogenously. This is important for our setting because even hotel customers benefit from Airbnb since they pay lower prices. Relatedly, Lam and Liu (2017) estimate a model of competition between Uber, Lyft, and taxis using data from New York.

Another related stream of work studies the role of peer-to-peer markets in enabling rental markets. The premise of these papers is that technology has made it easier to borrow and rent assets. Horton and Zeckhauser (2016) derive a theoretical model of equilibrium for assets and make predictions on the existence and size of rental markets across different product categories. Fraiberger and Sundararajan (2015) calibrate a model of car usage and make predictions on the reduction in car ownership as a result of peer-to-peer rental markets. Our work does not specifically study the decision to own or rent apartments, but it explicitly quantifies the benefits from renting on Airbnb.

Our paper is also complementary to existing studies of labor supply and market design on peer-to-peer platforms. We find that host supply is highly elastic on the margin. This is consistent with analysis of suppliers on Taskrabbit (Cullen and Farronato (2014)) and Uber (Hall et al. (2016), Chen and Sheldon (2015)). Other work on peer-to-peer markets has focused on the market design aspects of reputation systems (Fradkin et al. (2017), Nosko and Tadelis (2015), Bolton et al. (2012)), search (Fradkin (2015), Horton (2016)), and pricing (Einav et al. (Forthcoming), Hall et al. (2016)). Lewis and Zervas (2016) study the welfare effects of online reviews in the hotel industry. Finally, in our analysis of growth heterogeneity across cities, we contribute to the predominantly theoretical literature on technology adoption and diffusion (e.g. Bass (1969) and Griliches (1957)).

The paper is structured as follows. In the next section, we present the data and document geographic and time heterogeneity in the size of Airbnb, which motivates our theoretical framework for market structure with flexible and dedicated supply (Section 2.1). In Section 3 we test the basic predictions of our model on the long- and short-run elasticities of flexible supply, and on the spillover effects of Airbnb on hotels. Section 4 presents our empirical strategy for estimating the short-run equilibrium of our model. We discuss the estimation results in Section 5 and conclude in Section 6.

# 2 Motivation and Theoretical Framework

Airbnb describes itself as a trusted community marketplace for people to list, discover, and book unique accommodations around the world — online or from a mobile phone. The marketplace was founded in 2008 and has at least doubled in total transaction volume during every subsequent year. Airbnb has created a market for a previously rare transaction: the short-term rental of an apartment or room to strangers. In the past, these transactions were not commonly handled by single individuals because there were large costs to finding a match, securely exchanging money, and ensuring safety. While Airbnb is not the only company serving this market, it is the dominant platform in most US cities.[2] Therefore, we use Airbnb data to study the drivers and the effects of facilitating peer entry in the market for short-term accommodations.

Airbnb room supply has grown quickly in the aggregate, but the growth has been highly

[2] The most prominent competitor is Homeaway/VRBO, a subsidiary of Expedia. Its business has historically been concentrated in rentals of entire homes in vacation destinations, such as beach and skiing resorts.

heterogeneous across geographies. Figure 1 plots the size of Airbnb measured as the daily share of available Airbnb listings out of all rooms available for short-term accommodation.[3] Even among the top 10 cities in terms of listings, there are high growth markets like San Francisco and New York, as well as slow growth markets like Chicago and DC. This increase in available rooms is specific to the peer-to-peer sector and does not represent a broader growth of the supply of short-term accommodation (see Figure A1).

Within a city over time, there is also heterogeneity in the size of Airbnb relative to the size of the hotel sector. The fluctuations are especially prominent in New York in Figure 1, which experiences large spikes in available rooms during New Year's Eve, and in Austin during the South by Southwest festival. The figure suggests that market conditions during these spikes are especially suited to peer-to-peer transactions. These facts motivate our theoretical model, in which we distinguish between dedicated sellers (hotels) and flexible sellers (peer hosts).

## 2.1 Theoretical Framework

In this section, we introduce a theoretical model for understanding market structure with dedicated supply (hotels) and flexible supply (peer hosts) in the accommodation industry. We will test the predictions of this model in Section 3, and structurally estimate it in Section 4.

In our model, hosting services can be provided by professional and flexible sellers, who offer differentiated products. The model has a short and long-run component. The short-run equilibrium consists of daily prices and rooms sold of each accommodation type as a function of a demand state and the respective capacities of dedicated and flexible suppliers. We assume hotels are competing against a fringe of flexible sellers. The long-run component determines the entry condition of flexible sellers as a function of a fixed hotel capacity and the distribution of demand states.

We start by presenting the short-run equilibrium, which we view as an analog to daily market outcomes. We simplify the exposition by assuming that there is one single hotel and one undifferentiated type of Airbnb listings. In the empirical counterpart of this model presented in section 4, we relax this assumption. Let $K_h$ denote the existing dedicated capacity (number of hotel rooms), and $K_a$ the existing flexible capacity (Airbnb rooms). Demand state, $d$, is drawn from a distribution $F$, which can be interpreted as the distribution of demand states over the course of a year. Hotel rooms and Airbnb rooms are differentiated

[3] The total number of available rooms is the sum of available hotel rooms and listings available on Airbnb. The same heterogeneity is apparent if we adjust for capacity, or if we divide the number of Airbnb listings by the number of total housing units within an MSA.

products. $Q_i^d(p_i, p_j)$ is the residual demand for product $i$ as a function of its price and the price of the other product. $Q_i^d(p_i, p_j)$ is increasing in $d$ and $p_j$, and decreasing in its own price $p_i$.

The short-run sequence of events is as follows. Capacity $K_h$ and $K_a$ are given, demand state $d$ is realized, the hotel sets prices and at the same time Airbnb sellers choose whether to host. We assume that the hotel faces marginal cost $c_h$ to book one room for one night, and it sets its price to maximize profits subject to its capacity constraint:

$$\begin{aligned} \underset{p_h}{Max} \quad & Q_h^d(p_h, p_a)(p_h - c_h) \\ s.t. \quad & Q_h^d(p_h, p_a) \leq K_h \end{aligned} \tag{1}$$

Flexible sellers have unit capacity and variable marginal costs of renting their room. We assume that marginal costs of peers are randomly drawn from a known distribution, and that on average are higher than $c_h$. When choosing whether to rent our their room for a night, flexible producers take prices as given, and sell their unit if and only if the market clearing price is greater than their cost. The choices of individual hosts are aggregated to determine the total number of flexible rooms rented:

$$Q_a^d(p_a, p_h) = K_a Pr(c \leq p_a), \tag{2}$$

where $K_a$ is the mass of peer hosts, or total flexible capacity.

The market equilibrium consists of prices and quantities for the hotel and peers $(p_h, p_a, q_h, q_a)$ that equate flexible and dedicated room demand with flexible and dedicated supply.

The short-run model already offers some comparative statics predictions, listed below and proven in Appendix A. Under standard conditions, hotel profits per available room, as well as both prices and occupancy rates, are lower if $K_a$ is higher (Proposition 1 in the appendix). The separate effect of an increase in $K_a$ on hotel prices is higher if hotel capacity constraints are more often binding, but the opposite is true for the effect on occupancy (Proposition 2). Intuitively, this occurs because the increase in flexible capacity affects hotels through a reduction in their residual demand (Figure 2), and when hotels are capacity constrained, their supply curve is vertical (Figure 2a). A marginal downward shift in residual demand will have no effect on quantity and a large effect on price if supply is perfectly inelastic.

In the long-run, entry of flexible suppliers is endogenous. We assume that $K_h$ was optimally set knowing $F(d)$ and not expecting that Airbnb would lower entry costs of flexible sellers. Holding demand fixed, if investing in hotel capacity is more costly, optimal dedicated capacity is lower and expected profits per unit of capacity are higher.

A peer-to-peer platform enables the entry of flexible sellers. Flexible sellers decide whether to join the peer-to-peer platform and start producing as a function of expected demand. We assume that flexible sellers face a cost, $C$, of joining the platform, which is randomly drawn from a given distribution and that their time horizon coincides with the distribution of demand states $F$. Let $v_a = \int_d E_c \left( max\{0, p_a^d - c\} \right) dF(d)$. $E_c \left( max\{0, p_a^d - c\} \right)$ is the expected profit of a flexible seller given demand state $d$, and the expectation is taken over the distribution of marginal costs.

A flexible seller joins the peer-to-peer platform if $v_a \geq C$. If expected profits $v_a$ are higher, more flexible sellers will join the platform and start producing, and the share of flexible supply out of total supply will be higher. What affects $v_a$? The first element is the distribution of marginal costs $c$. Holding everything else constant, if the distribution of costs decreases in the sense of first order stochastic dominance, more peers will enter and start hosting. The second element is $p_a^d$, itself a function of $K_h$ and the distribution of demand $F(d)$. All else equal, a lower $K_h$ will increase equilibrium prices whenever capacity constraints bind, so it will increase the distribution of $p_a^d$ in the first order stochastic dominance sense. Clearly, a higher level of demand in every state is more attractive, but, perhaps less obviously, also an increase in demand variability is attractive for flexible suppliers. To explain why we can think of a simple mean-preserving spread of two demand states. In the low demand state, flexible suppliers host very few travelers in either case because hotels' low marginal costs imply low equilibrium prices. The difference occurs in high demand states. If the high demand state doubles, prices increase steeply, especially if hotel capacity constraints are hit, making it very attractive for flexible suppliers to host in periods of high demand. Appendix A formally states these comparative statics results in Proposition 3 and provides formal proofs. Section 3.2 confirms that these comparative statics predictions hold in the data.

One final aspect of our model is that it does not allow hotels to adjust dedicated capacity $K_h$ in response to peer entry. In the long-run, peer entry could partially crowd out dedicated sellers. Since our data only spans the first few years of Airbnb diffusion, we are unable to empirically capture hotels' capacity adjustments. Exploring the entry and exit decisions of dedicated producers would be a valuable extension of our work.

# 3 Data and Tests of the Model

In this section, we describe our data on Airbnb and hotels and document how it confirms the predictions of the theoretical framework. Our proprietary Airbnb data consists of information aggregated at the level of listing types. The variables we observe include the number of bookings, active and available listings, as well as average listed and transacted prices. An available listing is defined as one that is either booked through Airbnb or is open to being booked on the date in question according to a host's calendar. An active room is defined as a listing that is available to be booked on the calendar or is available for at least one date in the future.

We categorize Airbnb listings into four types: 'Airbnb Luxury', 'Airbnb Upscale', 'Airbnb Midscale', and 'Airbnb Economy'.[4] Listing types are defined using the following algorithm. We first run a city level hedonic regression of nightly price on listing fixed effects, date fixed effects, and bins for the number of five-star reviews.[5] Second, we extract the listing fixed effects and use Bayesian shrinkage to shrink fixed effects towards the mean. Third, we compute quartiles of listing quality and categorize a listing in a given quartile if its fixed effect plus review coefficient falls into the appropriate range. This procedure allows us to account for heterogeneity in Airbnb listing types without specifically modeling detailed geographic and room type characteristics at a city level.

The hotel data come from Smith Travel Research (STR), an accommodation industry data provider that tracks over 161,000 hotels. Our sample contains daily prices and occupancy rates for the 50 largest US cities for the period between January 2011 and December 2014.[6] STR obtains its information by running a periodic survey of hotels. For the 50 largest markets, 68% of properties are surveyed, covering 81% of available rooms. STR uses supplementary data on similar hotels to impute outcomes for the remaining hotels which are in their census but do not participate in the survey. The data is then aggregated to six hotel scales, from luxury to economy, which indicate the quality and amenities of the hotels.

Table 1 shows city-level descriptive statistics regarding hotels and Airbnb. In the average city, hotels charge $108 per room and their occupancy rate is 66%. Perhaps surprisingly, Airbnb has very similar transacted prices ($109) and much lower occupancy rates (15%). The within-city standard deviation of these outcomes varies greatly across cities. For example, the city at the 25th percentile has a standard deviation of hotel prices of $10 ($22 for Airbnb prices), while the city at the 75th percentile has a standard deviation of $21 ($34 for Airbnb prices). This indicates that markets differ not only in levels but in the extent to which conditions fluctuate within a year and over time.

During our sample period, Airbnb comprises a small share of the overall market as a percentage of total rooms available for short-term accommodation. The average Airbnb

[4]These categories are defined solely for the purpose of this paper and do not correspond to any metric used by Airbnb itself.

[5]The bins for the number of reviews are: 0, 1, 3, 5, 10, 25, 50, 100.

[6]The cities are ranked based on the absolute number of hotel rooms in 2014. See Census Database: http://www.str.com/products/census-database and STR Trend Reports: http://www.str.com/products/trend-reports

share of available rooms in the last quarter of 2014 is 2%, and in most cities it is between 1% and 3% (25th and 75th percentiles). Two other normalizations confirm that Airbnb was still small in most US cities by the end of our sample period. Across all cities, Airbnb rooms represent 4% of all guests and represent less than 1% of total housing units for all metropolitan statistical areas (MSAs) in our sample.

## 3.1 The Long-Run: Determinants of Peer Entry

In this section, we verify the theoretical predictions regarding the long-run growth of peer supply from Section 2.1. Although the theoretical model assumes that entry decisions are made instantaneously and jointly for all flexible sellers, in practice awareness about the Airbnb platform has slowly spread in our sample period, 2011 to 2014. We assume that the last quarter in 2014, the end of our sample, provides a valid approximation to the long-run share of peer supply derived in our model.

Figure 3 shows the relationship between Airbnb market share and hotel revenues per available room. Not surprisingly, the size of Airbnb is positively correlated with the average revenue per room in a city, with New York being both the city with the highest hotel revenues and the one with the highest penetration of peer hosts.

In Section 2.1 we presented our theoretical framework, which links the profitability of hosting for flexible sellers in a given city to the relative costs of hotels versus peer hosts. If hotels' investment costs are high or peer hosts have low marginal costs, profitability for peer hosts will be high. This implies more peer entry in cities with high hotel investment costs and low marginal costs of peers. We use two proxies for the first cost factor, i.e. hotel capacity investment costs. The first is the share of undevelopable area constructed by Saiz (2010). The index measures the share of a metropolitan area that is undevelopable due to geographic constraints, e.g. bodies of water or steep mountains. The second index is the Wharton Residential Land Use Regulatory Index (WRLURI), which measures the amount of regulation required for land use in each metropolitan area and is based on a nationwide survey described in Gyourko et al. (2008).[7] Figures 4a and A2 confirm that constraints to hotel capacity are correlated with Airbnb penetration in a city.[8]

The second cost factor influencing the viability of peer production is the marginal cost of peers. Although many factors affect the costs of hosting, we focus on those related to

[7] Saiz (2010) uses these two measures to calculate the housing supply elasticity at the level of a metropolitan area.

[8] Building restrictions also affect Airbnb supply through another channel, the cost of residential housing. There are greater incentives to monetize a spare bedroom when the costs of housing are higher, especially for liquidity constrained households. Figure A2 in the Appendix confirms a positive relationship between the share of household income used to pay rent in 2010 and the size of Airbnb in 2014.

demographics.[9] Households vary in their propensities to host strangers in their homes. For example, an unmarried 30-year-old professional will likely be more open to hosting strangers than a family with children. This occurs for at least two reasons. First, children increase a host's perceived risk of the transaction. Second, unmarried professionals are more likely to travel, creating vacant space to be rented on Airbnb. Figure 4b plots the share of flexible supply at the end of 2014 against the percentage of unmarried adults, while Appendix Figure A2 uses the percentage of children. The figures confirm that cities with more unmarried adults and fewer children are those where Airbnb has indeed spread more.

In addition to cost factors, our model predicts that travelers' demand affects peer entry. This is due to two related reasons. First, hotels typically do not have enough dedicated capacity to absorb all potential travelers in times of peak demand. In contrast, flexible sellers are able to provide additional supply during peak times, when their rooms are especially valuable to travelers. Second, since hotels must pre-commit to capacity and any adjustment in the form of new hotel buildings takes 3 to 5 years, unforeseen growth in demand will create an inefficiently low dedicated supply and will induce entry by flexible sellers.

We use data from air travelers to proxy for accommodation demand trends and fluctuations at the city-month level. Our data come from Sabre Travel Solutions, the largest Global Distribution Systems provider for air bookings in the US. We isolate trips entering a city as part of a round trip from a different city in order to measure the potential demand for short-term stays.[10] Figure 5a confirms the intuition that unexpected growth in demand will result in greater peer entry by showing that the 2012-2011 growth rate in travelers for each city is positively related to Airbnb penetration in 2014. Figure 5b plots the standard deviation of demand in 2011 and confirms that by the end of 2014 Airbnb is bigger in cities where the fluctuations in the number of arriving travelers are larger.

To conclude this section, we combine all the descriptive results into a regression. Table 2 displays the summary statistics for the cost and demand factors described above. Table 3 displays results from a regression where the dependent variable is the size of Airbnb in the last quarter of 2014 and the explanatory variables are combinations of the measures of relative costs, demand growth, and demand variability described above. We also control for market size in order to isolate the component of the standard deviation of demand which is due to demand variability. Despite the small sample size, column (1) shows that all factors affect the size of Airbnb in the expected direction, and two - peers' marginal costs, and demand volatility - are statistically significant. Column (2) adds an additional, and

[9]Other potential shifters of the returns to hosting include household liquidity constraints, building regulation and enforcement of short-term rentals, and the ease of vacating an apartment in high demand periods

[10]Observations in the underlying Sabre provides data on the number of passengers, the origin airport, and the destination airport for a given month. We aggregate these to an MSA-month measure of passengers.

potentially redundant measures of our proxies. The coefficients are in the expected direction for all proxies.

The last column of Table 3 suggests that demand proxies and hotel investment costs affect peer entry mostly through price. In column (3) we add the average revenue per room in 2011 as an additional control. We choose the 2011 average because it is not affected by subsequent peer entry. The coefficient on revenue per available room is positive and statistically significant. In addition, the coefficients on the demand and hotel investment cost proxies decrease in magnitude and become insignificant, which supports our theoretical model. Taken altogether, our proxies for the determinants of long-run peer supply explain almost 75% of the variation across the sample of 46 cities.

## 3.2 The Short-Run: Effects of Peer Entry on Hotels

In the previous section we have tested the long-run predictions of our theoretical model, those related to the entry of peer producers. Here, we take entry as given, and focus on the short-run drivers of peer supply, and the effects of peer supply on hotels. The awareness and diffusion process of Airbnb and its variation across cities help us identify the causal impact of Airbnb on hotel revenues.

First, we show how to properly measure the size of Airbnb, and how the short-run elasticity of Airbnb supply is twice as large as that of hotels. Then, we use an instrumental variable approach to study the reduction in hotel revenues caused by the entry of Airbnb, and its heterogeneity across cities and hotel scales.

### Measuring Airbnb Supply

We start by demonstrating how to properly measure Airbnb supply and studying how hosts flexibly respond to fluctuations in market-level demand over time. Figure 6 displays four measures of the size of Airbnb plotted over time: active listings, two measures of available listings, and booked listings. This figure displays three important facts. First, the share of active or available listings that are booked varies greatly over time. The booking rate is especially high during periods of high demand such as New Year's Eve and the summer. What we will show just below is that this is the result of a highly elastic peer supply. Second, the gap between active listings and available listings is increasing over time, suggesting attrition in active listings. Therefore, the meaning of an active listing does not stay constant over the entire period of study.

The third and most relevant fact from Figure 6 is that the number of unadjusted available listings (blue line) actually decreases during periods of high demand, most notably on New

Year's Eve. The main reason for this is that calendar updating behavior responds to room demand. Many hosts do not pro-actively take the effort to block a date on their calendar when they are unavailable (see Fradkin (2015) for evidence). However, when they receive a request to book a room, they often reject the guest and update their calendar accordingly. Since a larger share of listings receives inquiries during high demand periods, the calendar is also more accurate during those times. Therefore, the naively calculated availability measure suffers from endogeneity and is even counter-cyclical (high when demand is low, and low otherwise).

Since we need a measure of the size of Airbnb that stays stable over time, we create an adjusted measure of available listings. This measure includes any rooms which were listed as available for a given date or were sent an inquiry for a given date and later became unavailable. Therefore, it does not suffer from the problem of demand-induced calendar updating. It does overstate the "true" number of available rooms in the market, but as long as it overestimates true availability consistently over time we consider it to be the best measure of Airbnb size. Figure 6 displays our proposed measure (red line) against the naive measure of available listings (blue line). The new measure does not suffer from drops in availability during high demand periods. We use this measure throughout the rest of the paper unless otherwise noted.

**Peers' Responses to Demand Fluctuations**

From Figure 6 it is clear that Airbnb bookings fluctuate over time: more rooms are booked during the peak season than in other periods. In this section, we use 2SLS to document that flexible suppliers are almost twice as elastic as dedicated suppliers.

We estimate the average supply elasticity of hotel and Airbnb rooms with respect to their prices using the following equation:

$$log(Q_{mt}) = \chi log(K_{mt}) + \kappa log(p_{mt}) + \mu_{mt} + \epsilon_{mt}, \tag{3}$$

where $Q_{mt}$ is the number of (hotel or Airbnb) bookings in city $m$ and day $t$, $K$ denotes capacity, and $p$ is the average transacted price. The equation is estimated separately for hotels and Airbnb. $\kappa$ is the elasticity of supply with respect to prices, and will be different between flexible and dedicated supply. $\mu_{mt}$ includes city, seasonality (month-year), and day of week fixed effects to control for the fact that costs might change by city or over time (e.g., due to average differences in costs over cities or due to particular periods where hosts are less likely to occupy their residences).

This equation suffers from simultaneity bias because the price of accommodations is correlated with demand, and with unobserved fluctuations in marginal costs. Furthermore, in the case of Airbnb, the number of available rooms $K_{mt}$ is itself endogenous because hosts may list their room as available precisely during high demand periods.[11]

We discuss each concern in order. We instrument for price with plausibly exogenous demand fluctuations which are typically caused by holidays or special events in a city. We use two instruments. The first is the number of arriving (not returning) flight travelers in a city-month, which we used in Section 3.1. The second comes from Google Trends, which provides a normalized measure of weekly search volume for a given query on Google. Our query of interest is "hotel(s) $c$", where $c$ is the name of a US city in our sample. We de-trend each city's Google Trends series using a common linear trend to remove long-run changes in overall search behavior on Google. We use the one-week lagged search volume as an instrument, although using other lags or the contemporaneous search volume does not change the results.

To control for the fact that room availability on Airbnb is endogenous to demand, we instrument the number of available listings with a city-specific quadratic time trend. This instrument captures the long-run diffusion process of Airbnb and is uncorrelated with contemporaneous idiosyncratic shocks to supply. We use this same instrumentation strategy below to measure the effect of Airbnb supply on hotel revenues.

Table 4 contains our estimates of Equation 3 for Airbnb and hotels separately. Turning first to column 1, a 1% increase in the average hotel daily rate increases hotel bookings by 1.1%. This elasticity is just over half as large as that of Airbnb (column 2), whose estimated elasticity is 2.1. An important implication of this result is that smaller fluctuations in prices are needed for Airbnb supply to adjust upward or downward.

We have shown that the Airbnb supply is highly responsive to price, more so than hotels: a small price increase due to high demand greatly increases the number of booked rooms on Airbnb, and this increase is twice as large than for hotels. The lower elasticity of hotel supply has a simple explanation. To the extent that hotels have a constant marginal cost and a fixed supply, hotel bookings cannot increase in response to increases in demand when demand is sufficiently high. The higher elasticity of flexible supply implies that there are many hosts willing to rent their rooms when prices are high, but prefer not to host when prices are just a little lower. Our structural model rationalizes this result by estimating that there is a large mass of peers with costs close to the market clearing prices.

[11] We do not worry about the same endogeneity issue for hotels because hotel capacity is typically fixed in a 4-year interval, our sample period. However, instrumenting for hotel capacity with a quadratic time trend, as we do for Airbnb, does not change our results.

### Effects of Peer Entry on Hotel Revenue

In this section, we document the effects of peer entry on hotels' revenue, occupancy rates, and prices. Before describing our empirical strategy, we discuss the two most important challenges to identifying the effect of Airbnb. To do this, we consider the hypothetical scenario where Airbnb supply grows randomly across cities and over time. In this scenario, regressing the outcomes of hotels on the Airbnb supply would yield an unbiased estimate of the causal effect of Airbnb. However, as highlighted above, Airbnb does not grow randomly. In fact, Airbnb is larger in cities with high hotel revenues, and during periods of high demand within each city. Observables like the number of arriving flight travelers, city fixed effects, and seasonality fixed effects, help us control for this selection.

To account for idiosyncratic but predictable demand patterns such as holidays or festivals, which might affect the daily number of Airbnb listings, we instrument for the currently available Airbnb supply with a city-specific quadratic time trend. The time trend isolates the size of Airbnb due to its diffusion process and to long-run city characteristics but is independent of concurrent idiosyncratic demand shocks. [12]

Our baseline regression specification is:

$$y_{mt} = \alpha \log(airbnb_{mt}) + \beta \log(gtrend_{mt}) + \gamma \log(travelers_{mt}) + \theta_{mt} + \nu_{mt}. \tag{4}$$

Here $y_{mt}$ is one of three hotel outcomes (log revenue per available room, log price, occupancy rate) in a city $m$ on day $t$, $airbnb_{mt}$ is the number of available Airbnb listings, $gtrend_{mt}$ is the one-week lag of Google searches for hotels in the city, $travelers_{mt}$ is the number of arriving air passengers, and $\theta_{mt}$ includes city, quarter-year, and day of week fixed effects. Importantly, the Google metric captures demand shocks at the week level, while the number of incoming air passengers captures monthly fluctuations in demand. The fixed effects capture seasonality, differences across the days of the week, and time-invariant city characteristics that affect both the size of Airbnb and hotel revenue.

The effect of interest is $\alpha$, which is the average short-run elasticity of hotel outcomes to peers' supply over our sample period. The coefficient is identified off of two types of variation. First, there is variation across cities and over time in the number of available listings due to increasing awareness of Airbnb. Second, there is variation in the availability of listings due to hosts' daily costs of hosting, which we assume are uncorrelated with residual daily demand for accommodation within the city.

Table 5 displays the results of the baseline specification. The coefficient on Airbnb size in

[12] In Appendix B we conduct robustness checks to demonstrate that these controls and instruments likely capture potential sources of endogeneity.

column (1) is statistically significant and the estimated elasticity for hotel revenue is -.036. This coefficient implies that a 10% increase in available listings decreases the revenue per hotel room by 0.36%. The coefficient estimates for our demand proxies, Google trends and arriving air travelers, are of the correct sign and statistically significant. Once we break down the effect into a reduction in occupancy rates (column 2) and a reduction in prices (column 3), we see that on average Airbnb has a significant negative effect on prices but not on occupancy rates. Appendix B discusses the robustness of our finding to other measures of Airbnb supply and instrumentation strategies, and Table A4 separates the effect by hotel scale.

The fact that the effect of Airbnb on price (column 3) is the main reason for the decrease in hotel revenues confirms our intuitions from the model and our empirical evidence on long-run effects. On one hand, holding fixed Airbnb supply, our model predicts that in days and cities when hotels are not capacity-constrained, Airbnb should have a relatively bigger effect on occupancy than on price. The opposite is true when hotels are capacity-constrained: on those days, Airbnb should have a relatively bigger effect on price than on occupancy. On the other hand, we predicted and confirmed empirically that there will be more Airbnb rooms available in cities where hotels are often capacity constrained. Therefore, the coefficients are partially estimated from variation in Airbnb size in those cities, because in other cities the entry of Airbnb has so far been too limited to detect any impact.

To confirm this explanation, we divide our cities into two groups. Recall that our theoretical model from Section 2.1 predicts that the effect on price should be largest in cities with binding hotel capacity constraints. To test this, we split the sample into two groups and explore the heterogeneity of the effect of Airbnb across cities. Saiz (2010) uses the WRLURI and the share of undevelopable area described in Section 3.1 to estimate the housing supply elasticity at the city level. We take that supply elasticity as a proxy for the elasticity of hotel construction, and split our sample of cities at the median level of Saiz's estimates for the cities in our sample.

Table 6 displays the estimates of Equation 4 separately for the two groups of cities. Columns (1) and (4) display the estimates of the effect on revenue per available hotel room. Both coefficients on Airbnb are statistically insignificant. When we break the outcomes into prices and occupancy rates, we see that the statistically significant effect of Airbnb is a reduction in hotel prices in the capacity constrained cities (column 3). This is consistent with the fact that binding capacity constraints lead to spikes in hotel prices, which in turn attract more competition from Airbnb. In markets without building constraints, the supply of hotels should adjust so that hotels are pricing close to marginal cost at least some of the time. In constrained markets, hotels are often fully booked, and should be able to price significantly above marginal costs. When Airbnb enters, hotels face competition which decreases their peak prices without greatly affecting their occupancy rates.

Differences in the effect of Airbnb on hotels across constrained and unconstrained cities occur for two reasons. First, for the same level of Airbnb and hotel capacity, the effect of Airbnb is larger on prices if hotel constraints are more often binding (due to higher levels of demand). Second, for the same level of demand and hotel capacity, the effect on hotel revenues is larger if there are more Airbnb listings. Intuitively, the elasticity of hotel revenues with respect to the size of Airbnb should be higher, the higher the Airbnb share of supply because a 1 percent increase in Airbnb size is a much bigger share of market supply when Airbnb penetration is 3% then when it is 1%. Both conditions are true when we split our cities. Indeed, in December 2014 the average Airbnb supply share in supply-constrained cities was 4.3% while it was only in 1.4% in unconstrained cities. At the same time, the average hotel occupancy rate was 61% in constrained cities and only 53% in unconstrained cities.

To summarize Section 3, we have presented a series of tests of our theoretical model from Section 2. We documented that the entry of flexible capacity is responsive to long-run supply and demand characteristics. Flexible supply is more likely to enter in cities where hotels' fixed costs are high, where peers marginal costs are low, and where demand is increasing and highly variable. We have also shown that flexible supply is highly elastic, and almost twice as elastic as dedicated supply: a 10% price increase raises Airbnb bookings by 22%, against 11% for hotels. Finally, we have shown that the entry of flexible supply has negative spillovers on the revenue of dedicated suppliers. This negative effect is mostly due to competitive pressure on hotel prices and it is higher in cities with binding hotel capacity constraints. In the rest of the paper, we structurally estimate our short-run model in order to measure the welfare effects of Airbnb on consumers, peer hosts, and hotels.

# 4 Model and Estimation Strategy

In this section, we describe the fully specified short-run model that we estimate. This extends the theoretical model from section 2 to multiple hotel and Airbnb listing types. A market $n$ is defined by day, $t$, and city, $m$. On the demand side, our model is based on the random coefficients logit model of Berry et al. (1995), where rooms are differentiated across hotel scales and Airbnb listing types. On the supply side, we assume that hotels engage in Cournot competition with differentiated products across scales and identical products within scale. Airbnb hosts are price takers with randomly drawn marginal costs.

### Consumer Demand

Consumers make a discrete choice between hotel scales, Airbnb listing types, and an outside option for a given night. Consumer $i$ has the following utility for room option $j$ in market $n$:

$$u_{ijn} = \mu_{ijn} - \alpha(1 + \tau_{jn})p_{jn} + \epsilon_{ijn} \tag{5}$$

where $\mu_{jn}$ are market and option specific mean utilities for each accommodation (different hotel scales and Airbnb listing types), $p_{jn}$ is the price of an accommodation, $\tau_{jn}$ is the tax rate, and $\epsilon_{ijn}$ is a utility error with a type I extreme value distribution. We normalize the value of the outside option to $u_{i0n} = 0$ for all $n$. This demand specification yields the following quantities for each accommodation type:

$$Q_{jn}(p_{jn}, p_{-jn}) = D_n \int \frac{e^{\mu_{ijn} - \alpha(1+\tau_{jn})p_{jn}}}{1 + \sum_{j'} e^{\mu_{ij'n} - \alpha(1+\tau_{jn})p_{j'n}}} dH(\mu), \tag{6}$$

where $D_n$ is the market size, and $H$ is the joint distribution of consumer heterogeneity in $\mu_{ijn}$. We assume this distribution to be normal with mean vector and variance matrix to be estimated.

### Hotel Supply

Each hotel competes with other hotels of the same scale, hotels of different scales, and peer supply. We assume that this competition takes the form of a Cournot equilibrium. Hotels of type $h$, where $h \in \{$*luxury, upper-upscale, upscale, upper-midscale, midscale, economy, independent*$\}$, have aggregate room capacity $K_{hn}$. Since there are multiple hotels within each scale, we need to distinguish between scale-level and hotel-level quantities. We let $Q_{hn}$ denote the scale-level number of rooms sold. We assume no differentiation in room quality within scale, so the number of rooms sold by each hotel, denoted $q_{hn}$, is the ratio of aggregate quantity divided by the number of hotels. Analogously, scale-level capacity is denoted $K_{hn}$, while hotel-level capacity is $k_{hn}$.

We must also match the fact that prices increase sharply as the number of rooms sold approaches the number of available rooms. In practice, occupancy rates never reach 100% at the scale level, but prices start increasing before then (Figure 7). This is because, although we model hotels as homogeneous within each scale, some individual hotels may hit constraints before others and this may result in sharply increasing scale-level prices. In addition, if hotels face uncertainty about the actual level of demand when setting prices, increases in expected demand will increase the probability of hitting capacity constraints, thus increasing prices before realized demand reaches 100%. We allow our model to fit this increasing price profile by estimating an increasing cost function for hotels that occurs as soon as hotel occupancy is at least 85% within a scale. The estimation of increasing marginal costs as production approaches capacity constraints was previously used by Ryan (2012) to estimate the cost structure of the cement industry.

Following Ryan (2012), we assume that hotels' variable costs are made of two parts: a constant marginal cost $c_{hn}$, and an increasing marginal cost $\gamma_{hn}(q_{hn} - \nu k_{hn})$, which starts binding as quantity approaches the capacity constraint. So, instead of solving a maximization problem subject to a capacity constraint as in Equation 1, each hotel selects its quantity to maximize the following profit function:

$$\underset{q_{hn}}{Max}\ q_{hn} p_{hn}(Q_{hn}, Q_{-hn}, Q_{an}) - q_{hn} c_{hn} - \frac{\gamma}{2} \mathbb{1}(q_{hn} > \nu k_{hn})(q_{hn} - \nu k_{hn})^2.$$

Letting $N_{hn}$ denote the number of hotels within scale $h$, we have that $q_{hn} = \frac{Q_{hn}}{N_{hn}}$. Taking advantage of the implicit function theorem, the optimization problem gives rise to the following first order condition:

$$p_{hn} = -\frac{1}{N_{hn}} \frac{Q_{hn}}{Q'_{hn}} + c_{hn} + \gamma \mathbb{1}(q_{hn} > \nu k_{hn})(q_{hn} - \nu k_{hn}), \tag{7}$$

where $Q_{hn}$ is scale-level room demand, and $Q'_{hn}$ is the derivative with respect to its own price.

### Peer Supply

Peers of each quality type $a$ with total available listings $K_{an}$, take prices as given. Hosts draw marginal costs from a normal distribution with parameters $\omega_{an}$ and $\sigma_{an}$. Each draw is iid across hosts and time. Hosts of type $a$ choose to host only if the price $p_{an}$ is greater than their cost. Therefore, the quantity supplied will be determined by the following equation:

$$Q_{an}(p_a, p_{-an}, p_{hn}) = K_{an} Pr(c \leq p_{an}) = K_{an} \Phi\left(\frac{p_{an} - \omega_{an}}{\sigma_{an}}\right). \tag{8}$$

As in the case of hotels, this equation is the extension of Equation 2 with multiple types of hotels and Airbnb listings.

### Equilibrium

The market equilibrium consists of prices and quantities for hotels and peer hosts ($p_{hn}, p_{an}$, $Q_{hn}, Q_{an}$) such that consumers, hotels, and peer hosts make decisions to maximize their surplus, and their optimal choices are consistent with one another.

## 4.1 Estimation Strategy

We estimate the demand and hotel supply models jointly, and peer supply separately. The high-level choices in this model are the moments to match, the market size, the degree of unobserved consumer preference heterogeneity, and the instruments used.

First, a normalization is needed. Since Airbnb listings are on average bigger than hotel rooms and can host more guests, we adjust quantities so that room capacity is comparable across Airbnb listings and hotel rooms. To do this, we take advantage of the fact that we have information on the average number of guests for Airbnb transactions. In addition, lower quality Airbnb listings are typically private rooms with similar capacity as standard hotel rooms. For this reason, we assume that each hotel room is occupied by as many people as the average number of occupants of Airbnb listings in the midscale quality category in the same city. Given this adjustment, our quantities, prices, and estimates should be interpreted as referring to room-nights with standard hotel occupancy.

Our demand model is a logit model with a normally distributed random coefficient on the inside option and a random coefficient on hotel scale (Berry et al. (1995)) . The standard deviation of the normal distribution, which we estimate, is denoted $\Sigma$. We use data on the 10 largest cities in terms of the share of Airbnb bookings in our sample. Our initial estimation sample includes all Saturdays in 2013 and 2014. We later use these estimates to compute counterfactual for all days of the week. The main reason for restricting the sample to 10 cities and the two most recent years in our data derive from the fact that in other cities and time periods market shares of Airbnb are often close to zero, which complicates our estimation. For the same reason, we also drop Airbnb options if their share of available rooms is less than 1% on a given day and city.

One choice we must make in the estimation is $D_n$, the total number of consumers considering to book accommodations. The choice of $D_n$ will affect market shares for hotels and Airbnb, as well as the share of potential travelers choosing to stay home, to travel to other locations, or to stay in alternative accommodations, e.g. staying with friends and family. We set $D_n$ equal to three times the average number of rooms booked in the corresponding month in each city in 2012. This assumption allows the potential number of travelers to vary seasonally across cities, and it allows for both substitution from hotels – hotel travelers switching to Airbnb –, and market expansion – travelers switching from the outside option to Airbnb.

With the assumptions outlined above, we construct three sets of moments: moments to match predicted and realized market shares (demand moments), moments to match predicted hotel-Airbnb substitution with substitution obtained from survey responses (substitution moments), and moments to match predicted and realized prices (supply moments).

Our demand moments are

$$m_{1jn} = \left[\delta_{jn} - \hat{\delta}_{jn}\right] Z_{1jn}, \tag{9}$$

where $\delta_{jn}$ is the realized mean utility from accommodation $j$ in market $n$ that rationalizes the observed market shares, and $\hat{\delta}_{jn}$ is the mean utility predicted from the vector of parameters to be estimated. We parametrize $\hat{\delta}_{jn} = -\alpha(1 + \tau_{jn})p_{jn} + \beta X_{1jn}$. $\hat{\delta}_{jn}$ is the component of utility that does not differ across individual travelers. $X_{1jn}$ includes observable shifters of demand for relative types of accommodation: city-scale fixed effects, city-month fixed effects (to account for market specific seasonality), the log of Google searches and its square, the log of Airline passengers and its square, a linear time-trend, and an Airbnb specific linear time-trend.

We generate instruments in the following manner. First, we use a series of cost-shifters that affect prices without being correlated with demand shocks. These cost-shifters include hotel and Airbnb tax rates,[13] changes in the wages of maids and clerks, and the number of residents traveling out of a city (an Airbnb supply shifter). An additional variable that affects price, but is uncorrelated with short-term demand shocks is the total number of available rooms. We first interact the predicted number of active Airbnb listings with an indicator variable for hotel and vice versa. This represents a competition instrument. Second, the number of rooms within a scale represents the hotel's capacity constraint. To use it as an instrument, we interact it's inverse (and it's square) with the Google Trends demand proxy (and it's square). This nonlinearity is important to include because capacity constraints affect prices more when demand is higher. Due to the fact that we have many instruments which are potentially weak and correlated with each other, we take the principal components of the instruments and keep the components that account for 99% of the variation (Carrasco (2012)). Next, we use the components to predict observed after-tax prices.

Once we have predicted prices from the set of instruments presented above, we follow Gandhi and Houde (2016) and compose additional instruments that measure the distance in characteristic space between different accommodation options. The relevant characteristics in our model include scale and price. Our instruments include: the difference and square of the difference between the predicted price of an option and the predicted price of its closest alternatives (for midscale hotels, the closest alternatives are upper midscale and economy), the total number of options whose predicted price is within a standard deviation of an option predicted price, and the sum and sum of squares of the difference between the predicted price of an option and the predicted price of hotel options. We describe the instruments in greater

[13] Airbnb started collecting occupancy taxes in Portland, OR on July 1, 2014, and began collecting taxes in San Francisco on October 1, 2014.

detail in Appendix C.

The substitution moment comes from survey data on alternative accommodation choices of travelers booking on Airbnb. In 2015, Morgan Stanley and AlphaWise conducted a representative survey of 4,116 adults in the US, UK, France, and Germany. In the survey, they asked respondents about their travel patterns.[14] 12% of respondents had used Airbnb within the past year and when asked which travel alternative Airbnb replaced, 42% of respondents answered a hotel. We match this moment in our model by computing the share of Airbnb bookings that would result in hotel bookings at the observed equilibrium prices if Airbnb was not available. To predict the share of Airbnb travelers choosing hotels in the absence of Airbnb, we first note that Airbnb market share in market $n$ is $s_{airbnb,n} = \sum_{j \in \text{airbnb}} \int \frac{e^{\mu_{ijn} - \alpha p_{jn}}}{1 + \sum_{j'} e^{\mu_{ij'n} - \alpha p_{j'n}}} dH(\mu)$. The integral is taken over the distribution of the random coefficients. Hotels' market share is $s_{hotels,n} = \sum_{j \in \text{hotel}} \int \frac{e^{\mu_{ijn} - \alpha p_{jn}}}{1 + \sum_{j'} e^{\mu_{ij'n} - \alpha p_{j'n}}} dH(\mu)$, and hotels' market share if Airbnb was not available is $s_{hotels,n^*} = \sum_{j \in \text{hotel}} \int \frac{e^{\mu_{ijn} - \alpha p_{jn}}}{1 + \sum_{j' \in \text{hotel}} e^{\mu_{ij'n} - \alpha p_{j'n}}} dH(\mu)$. Aggregating over all markets gives us the following moment:

$$m_{2n} = \sum_n \left[ D_n * \left( \frac{s_{h,n^*} - s_{h,n}}{s_{a,n}} - s_{survey} \right) \right]. \tag{10}$$

The last set of moments comes from the supply side pricing decision:

$$m_{3jn} = [p_{jn} - \hat{p}_{jn}] \, Z_{2jn}, \tag{11}$$

where the predicted price comes from the hotels' profit-maximization problem and is equal to $\hat{p}_{jn} = -\frac{1}{N_{hn}} \frac{Q_{hn}}{Q'_{hn}} + \theta X_{2hn} + \gamma_{jn} \mathbb{1}(q_{hn} > \nu k_{hn})(q_{hn} - \nu k_{hn})$. $X_{2hn}$ includes city-scale fixed effects and city-specific linear time trends. Furthermore, we allow the increasing cost parameter, $\gamma$, to also vary by city and scale.

We include several instruments. First, in order to estimate the linear costs, we include city by scale fixed effects and city specific time trends. Second, we add demand shifters. These include city by month fixed effects, which capture seasonality, and interactions between Google Trends and city by hotel fixed effects, which approximate the increasing cost function. We also include the inverse of the number of available hotels, and the ratio of Google trends to the number of available hotels and rooms. These instruments are included because they are correlated with the endogenous components of the cost functions (e.g. the markup and $(q_{hn} - \nu k_{hn})$) but are not determined by the price set by the hotel on a given night.

We use moments in equations 9, 10, and 11 and estimate the set of parameters $(\beta, \alpha, \Sigma, \theta, \gamma)$

[14] See Nowak et al. (2015).

by generalized method of moments. We use data from Saturday nights only. We then assume that for other days of the week the price coefficient $\alpha$, as well as the degree of consumer heterogeneity $\Sigma$ are equal to those estimated for Saturday nights. This allows us to estimate the other parameters, $(\beta, \theta, \gamma)$, separately for each day of the week.

Lastly, the supply of Airbnb can be estimated separately using a linear instrumental variables regression. Equation 8 implies that $\Phi^{-1}\left(\frac{Q_{an}}{K_{an}}\right) = \frac{\omega_{an}}{\sigma_{an}} + \frac{1}{\sigma_{an}} p_{an}$, where the left-hand side is the inverse of a standard normal CDF calculated at a value equal to the share of booked rooms out of all Airbnb listings. We estimate this equation separately for each listing type using the following specification

$$\Phi^{-1}\left(\frac{Q_{an}}{K_{an}}\right) = \beta_a p_{an} + \gamma_a X_{an} + \epsilon_{an}, \tag{12}$$

where $K_{an}$ is the number of active Airbnb listings, $p_{an}$ is the average transacted price of Airbnb type $a$ in market $n$, and $X_{an}$ include year-month fixed effects, city fixed effect, and city-specific linear time trends. The transacted price is instrumented with the one-week lag of Google search trends and the log of incoming air passengers.

After estimating the above equation, we can transform the coefficients into the peers' cost parameters to estimate:

$$\sigma_{an} = \frac{1}{\beta_a}, \; \omega_{an} = \frac{\gamma_a X_{an} + \epsilon_{an}}{\beta_a} \tag{13}$$

# 5 Results

In this section, we discuss the results of our estimation. We first go over our estimated parameters. Then we discuss the effects of Airbnb on consumer surplus. Lastly, we study the effects on hotels' and hosts' bookings, revenues, and surplus. For each of these outcomes, we discuss heterogeneity across cities and time periods.

## 5.1 Parameter Estimates

Table 7 displays the common coefficient estimates across cities. Turning first to the coefficient on price, we find a coefficient of -.014, which is in line with estimates for the hotel sector in Koulayev (2014). We find that demand increases over time and especially so for Airbnb options. Our demand proxies, namely the Google Trends searches and the airline travelers have the expected signed coefficients. Lastly, we estimate a positive and statistically significant random coefficient on the inside option. This parameter is especially important because it governs the extent to which Airbnb travelers would substitute towards hotels or the outside option if Airbnb were not to be there.

Next, we consider the average willingness to pay of travelers across options. Figure 8 displays the mean dollar value per night of each option in each city at the end of 2014. Our estimates show that willingness to pay tends to be decreasing between luxury and economy hotels and between luxury and economy Airbnb listings. The fact that some mean values are negative reflects our choice of the normalization of the outside option. The value of the top Airbnb option is lower than the value of economy hotels across all cities, with some variation in the relative differences by city. There are several potential explanations for this variation including differences in traveler attention, traveler types and the quality of listings across cities. We do not distinguish between these explanations in this paper.

There is also dispersion in the quality of Airbnb rooms, with 'Luxury' Airbnb room types being valued more than $100 more per night than 'Economy' Airbnb rooms.[15] Lastly, Table A5 shows the city specific own price elasticities across options. We find that demand for accommodations is elastic on average. For example, in New York, the demand elasticities range from -6.2 for luxury hotels through -2.3 for economy hotels. There is also substantial variation across cities in demand elasticities, ranging between -2.9 and -1.3 for midscale hotels.

Next, we turn to the hotel and peer cost estimates. Table A6 displays the constant component of the hotel cost functions. We find that the marginal costs of hotels typically have the expected relationship with the hotel quality. Luxury hotel costs in New York city are $298 on average. Note that these costs do not represent the actual incurred expenses made by the hotel per night booked. Hotels often have a minimum price below which they will not price because of reputation costs (Kalnins (2006)). Instead, we view our estimated costs as an approximation of the as-if costs used by hotels when choosing their prices. Table A7 displays the increasing marginal cost component of the hotel pricing function. We find that for all but one of the city and hotel combinations, marginal costs increase with the quantity when the hotel's occupancy is above 85%. This increasing cost reflects the fact that, even when competition is high, hotels will shade their prices upward as they approach full capacity. Figure 9 displays the estimated marginal cost curves for hotels across cities within scale and across scales within New York. These figures illustrate the steep increase in marginal costs as a function of quantity that occurs for virtually all hotel scales in our sample once occupancy is high.

[15]The naming of Airbnb listings as 'Luxury' through 'Economy' is not meant to make them directly comparable to similar hotel room types. Each Airbnb listing quality type corresponds to one of four quartiles of Airbnb room type qualities as derived from hedonic price regressions.

Table A8 displays the estimated mean and standard deviation of the cost distribution for Airbnb hosts across cities. The mean costs range from $64 for the lowest quality rooms in Portland to $240 for the highest room types in Miami. For all cities, costs increase monotonically in listing quality. Furthermore, for all room types, the mean costs exceed the mean prices at which listings transact. We also estimate economically and statistically significant dispersion in the cost distribution for all listing types.

These relatively high costs stem from the fact that fewer than 50% of active listings on Airbnb typically transact (See Table 1). The model matches this fact by estimating a high mean cost. A more theory oriented explanation is that the marginal host being booked is just indifferent between hosting and not hosting. Otherwise this host would've lowered their posted price. Consequently, there is a large share of hosts that are only willing to host when market clearing prices are relatively high.

Figure 10 displays the mean costs over time for listings in New York City. There is variation in these costs and a slight increasing trend across room types. Interestingly, costs go up during New Years and high travel periods in the fall. This may reflect the fact that people traveling to New York City during those times are higher cost due their increased potential to be disruptive. Alternatively, it may mean that the full-time residents or owners of these listings may prefer being in New York City during these time periods.

### 5.2 Consumer Surplus

In this section we discuss consumer surplus from Airbnb. We present two counterfactual scenarios that remove Airbnb as an accommodation option and sequentially incorporate hotels' price adjustment decisions, which are driven by their capacity constraints. Table 8 displays the consumer surplus results for 2014.

Our first counterfactual scenario represents a scenario where Airbnb is not available and those who booked on Airbnb could book any hotel regardless of capacity constraints. We refer to this case as 'Unconstrained'. Table 8 shows there would be a $305 million loss in consumer surplus under this scenario. Table 9 shows that this loss equals $49 per night booked, or a total of 35% of the purchase price. The consumer surplus gain in this scenario only measures one channel, the benefit of having Airbnb as a differentiated product at the equilibrium prices.

Our second counterfactual, which we call 'Price Adjustment', allows hotels to re-optimize their prices to account for the absence of the Airbnb option. Relative to the previous counterfactual, there are two additional mechanisms in this scenario. First, those who previously booked Airbnb now face hotels with a higher price. Second, those who previously booked at hotels face higher prices. The consumer surplus gain in this scenario is $432 million or $70 per night booked.

We can also look at the heterogeneity of consumer surplus gains across cities and time periods. The total surplus from Airbnb is primarily determined by the number of Airbnb bookings in that city. This means that the greatest gains are in New York, Los Angeles, and San Francisco. The surplus per booking is greatest for Seattle and lowest for New York.

Lastly, we can look at how the consumer surplus gains are split across 'compression nights', which are nights where the hotel occupancy is at least 95%. The consumer surplus on constrained days is shown in the last row of Tables 8 and 9. On these nights, the difference in surplus between the unconstrained and price adjustment counterfactuals is especially large, with a difference of $36 per night on compression nights and a difference of $20 per night on average across all nights.

## 5.3 Hotel Surplus

We now turn to the effects of Airbnb on the hotel sector. Table 10 displays the counterfactual outcomes for hotels in terms of both bookings and revenues. Across all cities, the number of hotel nights booked would decrease by .57% without Airbnb and revenue would decrease by 1%. This corresponds to a loss of $269 million in revenue.

The effects of Airbnb on hotel revenues are also heterogeneous across cities and over time. For example, in New York, bookings would increase by .75% and revenue would increase by 1.5% without Airbnb. In contrast, in San Jose, a relatively unconstrained city, bookings would increase by .22% and revenues would increase by .26% when Airbnb is removed from the market and hotels are allowed to readjust prices. There is also heterogeneity in effects on compression nights. Hotel bookings fall by just .27% on compression nights but revenues fall by .97%. This demonstrates that Airbnb's effect on hotel's prices is larger and more skewed towards price on high demand days in constrained cities. We can also look at the effect of Airbnb on hotel profits, which we calculate as hotel revenue minus the non-increasing part of the cost function. We find that profits fall by 3.1% on average across all of the cities in the sample, with the largest fall coming in New York.

Note that the profit numbers above do not directly correspond to hotel surplus. This is for at least three reasons. First, hotels also earn revenue through complimentary services such as the hosting of conferences and food sales. We do not have the data on these income sources. Second, there are fixed costs involved in operating a hotel which we do not model in this exercise. If competition from Airbnb is strong enough, then some hotels may close down or new hotels may not be built. Third, our marginal cost estimates correspond in part to reputation costs rather than 'true' marginal costs. Consequently, hotels' variable profits are likely to be larger than what we've estimated.

Next, we consider the extent to which Airbnb expands the market vs cannibalizes hotel demand. Table 11 displays results regarding the share of Airbnb bookings that would not have resulted in a hotel booking under different counterfactual scenarios. In the scenario where we do not impose constraints, between 59% and 64% of Airbnb bookings would not have resulted in a hotel booking. This is consistent with the survey moment that we use in the data. These market expands effect becomes bigger when we impose capacity constraints and price adjustment. The share of market expanding Airbnb bookings in the price adjustment counterfactual range from 71% in San Jose to 86% in New York.

## 5.4 Peer Producer Surplus

Peer hosts represent the last agent type affected by the spread of peer-to-peer marketplaces. Below, we discuss the estimated peer costs and surplus. Recall that we assumed the costs are normally distributed. Our estimation procedure recovers a mean cost for every day, city, and listing type. We also estimate a standard deviation of listing costs which is constant across cities but changes by listing type.

Next, we use the cost distributions of hosts to back out the surplus that they receive from hosting. The surplus for each day can be calculated using the following expression, where we censor the cost distribution at 0.

$$PS_{an} = \int_{-Inf}^{p_{an}} (p_{an} - max(c, 0)) dF_{an}(c) \tag{14}$$

Note that this expression ignores the variable costs of being listed for a given day, which are likely to be negligible, and the fixed costs of entry into the platform.

Table 12 displays average surplus per booking and total surplus in 2014. The typical surplus per night ranges between \$26 in Las Vegas and \$30 in Austin. Across all bookings in these cities, the average surplus is \$27 and does not vary much across high and low demand days. Column 3 displays the total peer producer surplus in millions of dollars in each city. New York City hosts (\$8 million), followed by Los Angeles (\$3.3 million) and San Francisco (\$2.9 million), enjoyed the greatest benefit from hosting. In total across cities, host surplus was \$20 million and 45% of this surplus comes on compression nights.

# 6 Conclusion

We have studied the economics of peer production in the short-term accommodation industry. We first documented the determinants of peer supply. We showed how market-specific factors such as supply constraints and the costs of hosting affect whether peer production is viable in a given city. We then documented that peer supply is highly responsive to changes in market demand conditions in the short-run. This motivated a reduced form specification which we use to study the effects of Airbnb on the hotel sector in major US cities. We found that a 10% increase in the number of available Airbnb listings decreased hotel revenue by an average of .36%. This effect varies across cities and listing types. It is larger in cities with constrained hotel supply and is not concentrated solely on economy hotels.

Next, we developed a structural model of short-run equilibrium in this industry and used it to study the surplus and market expansion effects of Airbnb. We find that peer production generates $70 of surplus per night booked in 2014. This surplus comes both from new bookings generated by Airbnb and from lower prices paid by those who book hotels. In total, Airbnb generates $432 million in consumer surplus in 2014 for 10 large US cities.

The spread of Airbnb has also affected producers. We find that without Airbnb on these days, hotel revenue from bookings would be .57% higher. Nonetheless, over 70% of nights booked on Airbnb would not have resulted in a hotel booking in the absence of Airbnb. These travelers would have instead chosen the outside option, which could represent staying with friends or family, staying at a non-hotel accommodation, booking fewer nights, or not traveling to the city at all. Peer production also benefits the peers who are hosting Airbnb guests. We find that the average surplus per night from hosting is $28, which totals to $20 million in these cities for 2014.

Our data only extend through the end of 2014. Since then, Airbnb has continued its rapid growth in both active listings and global awareness. While we cannot say how large its effects have been since then, our paper documents two fundamental reasons why peer production is valuable in the accommodations industry. First, peers offer a differentiated product that is not a perfect substitute to hotel rooms and is valued by consumers. Second, the hotel sector in many cities is frequently constrained and cannot accommodate all potential travelers during peaks in demand. These constraints give hotels market power, which results in large prices increases. Peer production becomes viable at exactly these times, and reduces hotel pricing power.

We have focused on the effects of a peer-to-peer platform on the agents directly involved: hotels, peers, consumers. However, this new form of production can have externalities and important spillovers into other markets including the labor and housing markets. Furthermore, the platform also generates surplus from the market. We leave the study of these effects for future work.

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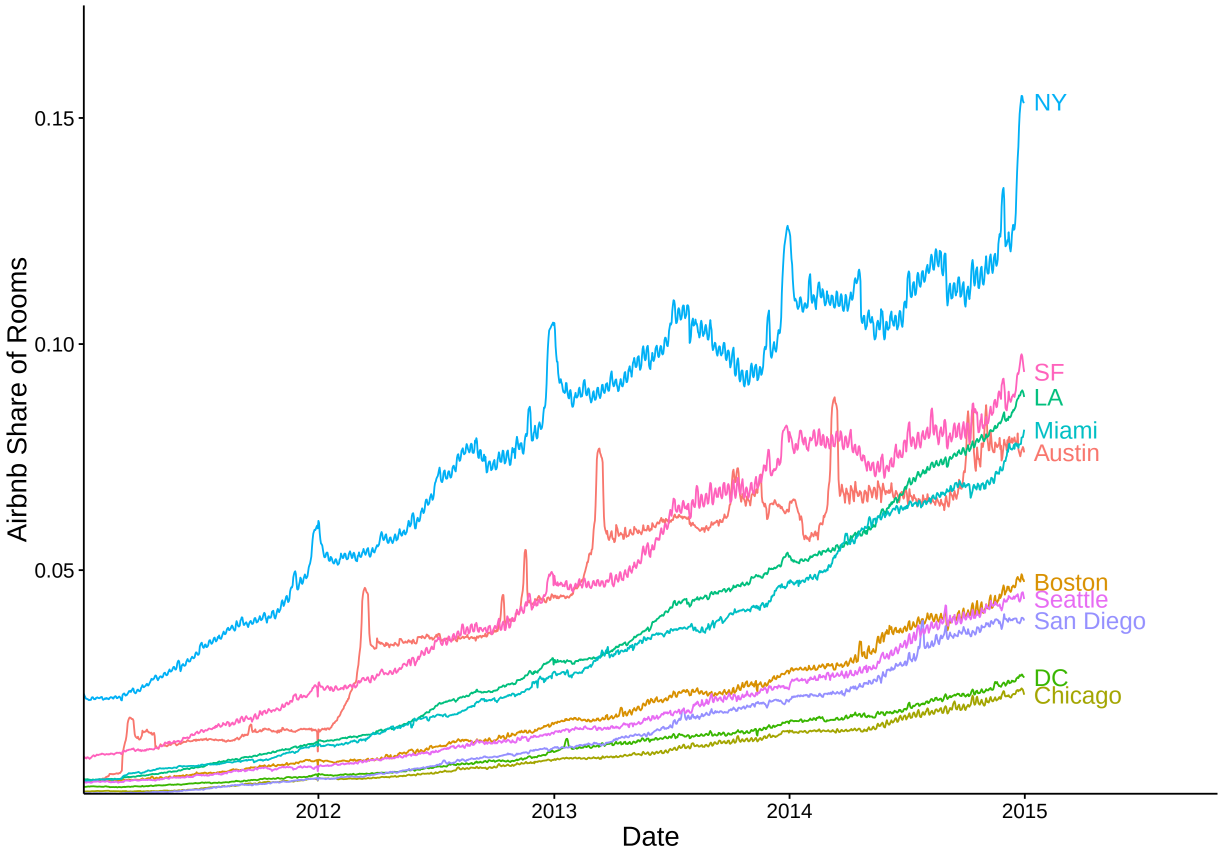
# Figures

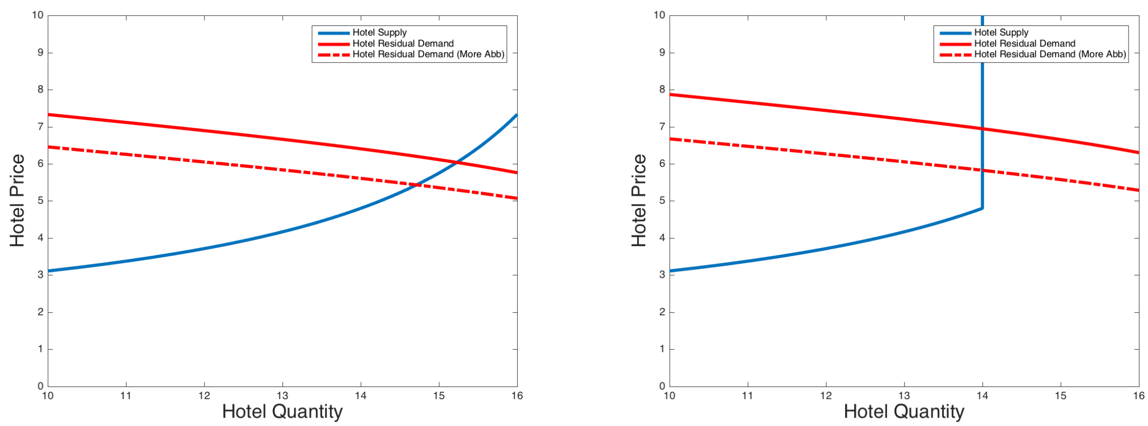
Figure 1: Growth of Airbnb




*The figure plots the size of Airbnb over time in 10 selected cities. The y-axis is the monthly average of the daily share of Airbnb listings out of all (hotel and Airbnb) rooms available for short-term accommodation. The 10 selected cities are those with the largest number of listings on Airbnb as of December 2014 among the 50 US major cities.*

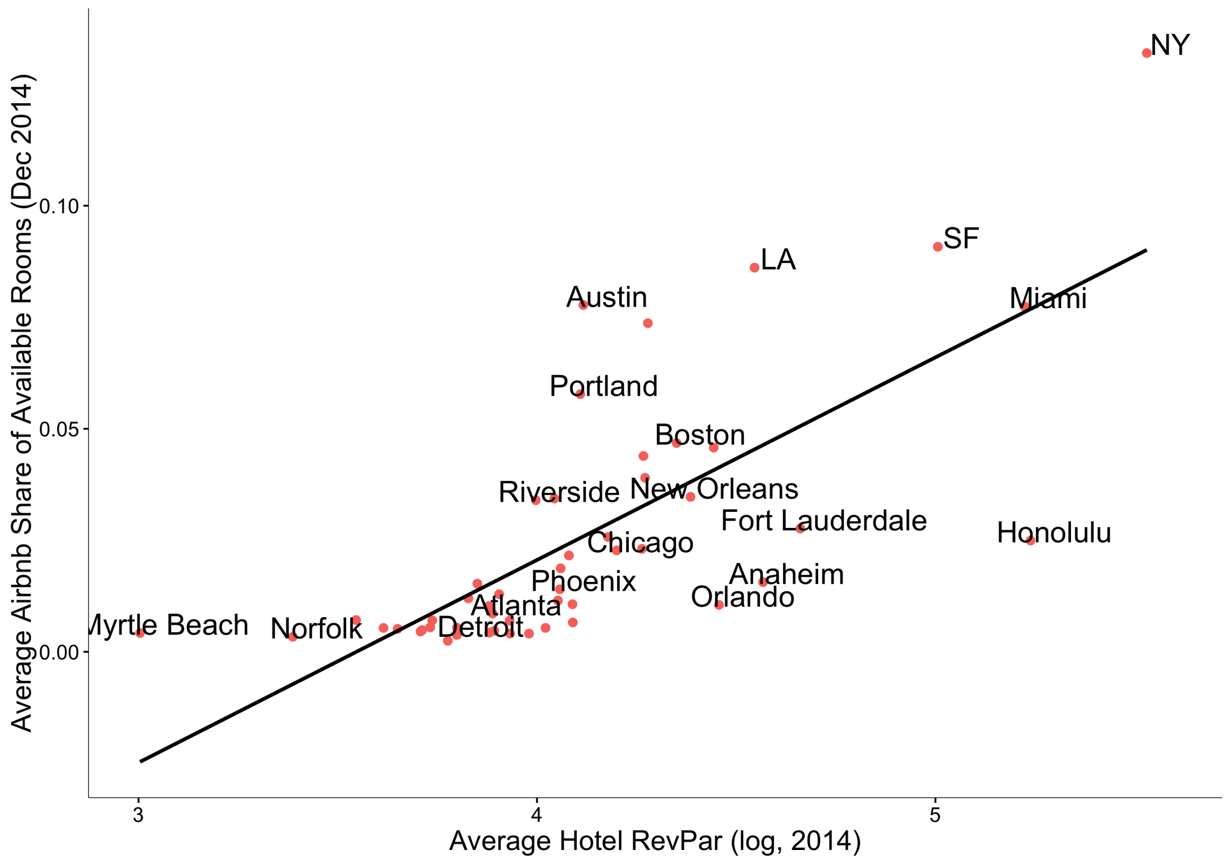
Figure 2: Predictions on the Effect of Airbnb Supply on Hotels

(a) Unconstrained Equilibrium (b) Constrained Equilibrium




*The figures plot the supply and demand curve for hotel rooms in two scenarios. The left panel displays an unconstrained equilibrium, while the right panel displays an equilibrium where the hotel capacity constraint is binding. Peer entry represents a downward shift in demand for hotel rooms. This downward shift will affect hotel quantity relatively more when the hotel supply curve is more elastic. The opposite is true for the effect on hotel prices, which is higher in the capacity-constrained equilibrium.*

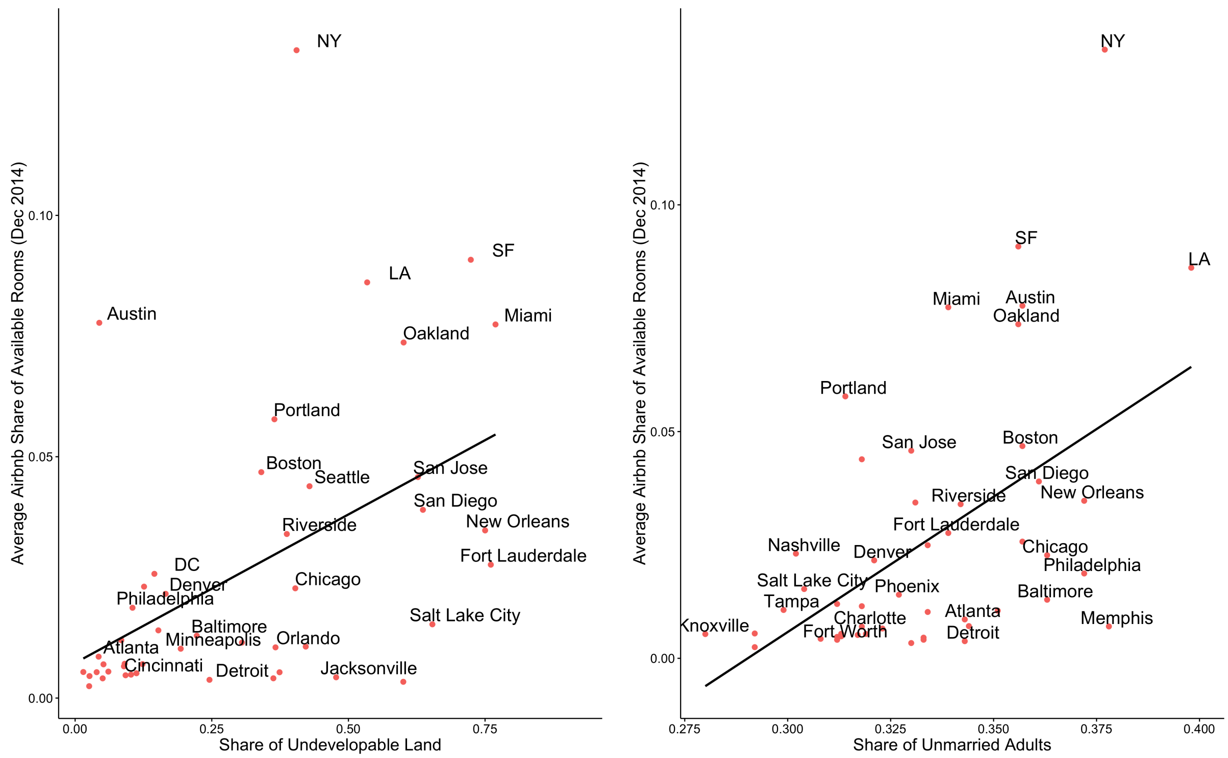
Figure 3: Peer Production and Hotel Revenues




*This figure plots the supply share of Airbnb against the average revenue per available room in each respective city.*

Figure 4: Peer Production and Fixed or Marginal Costs

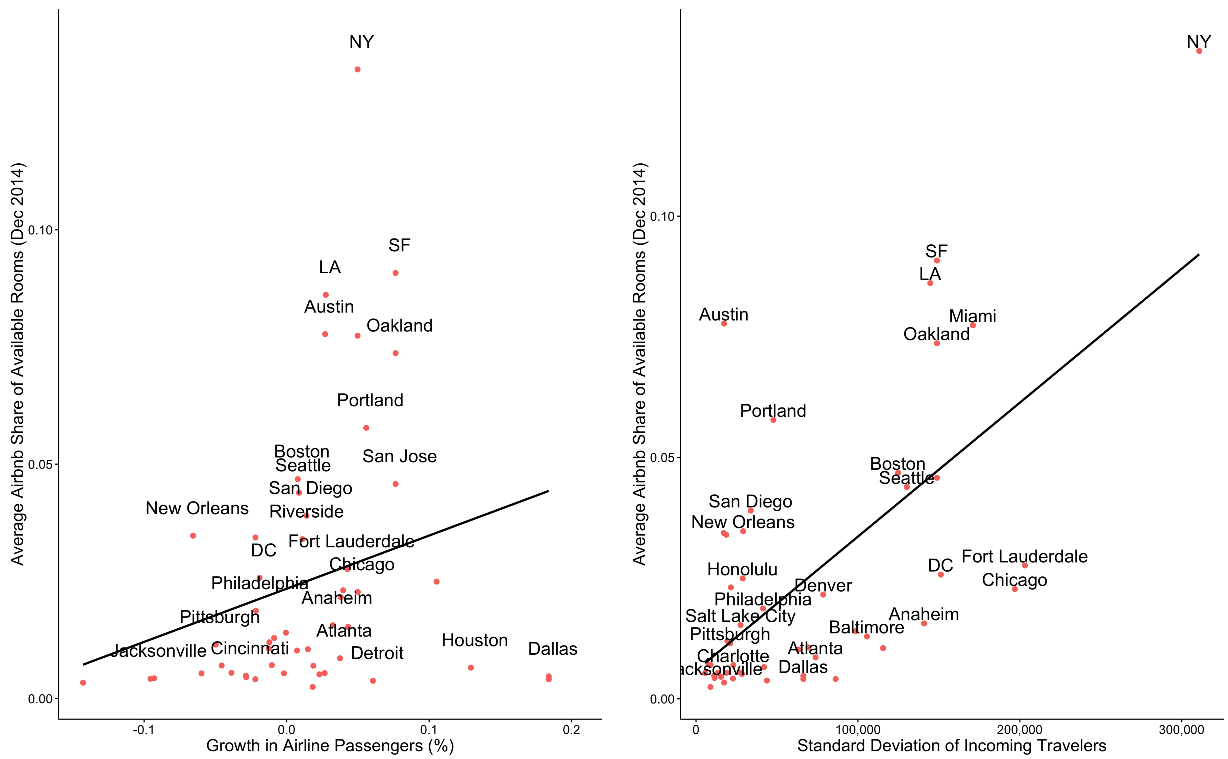
(a) Hotel Supply Constraints (b) Peers' Marginal Costs




*The figures plot the size of Airbnb against a proxy for hotel investment costs (left panel) and a proxy for peers' marginal costs (right panel). The proxy for the constraints to the construction of new hotels is the share of undevelopable area developed by Saiz. This index measures the share of a city that is undevelopable due to geographic constraints, like steep mountains or the ocean. The proxy for peers' marginal costs is the share of unmarried adults in the MSA. The size of Airbnb is measured as the average share of available listings in the last quarter of 2014. Figure A2 in the Appendix confirms that other proxies such as regulatory constraints, the share of children, and the rent to income ratio are also good predictors of peer entry.*

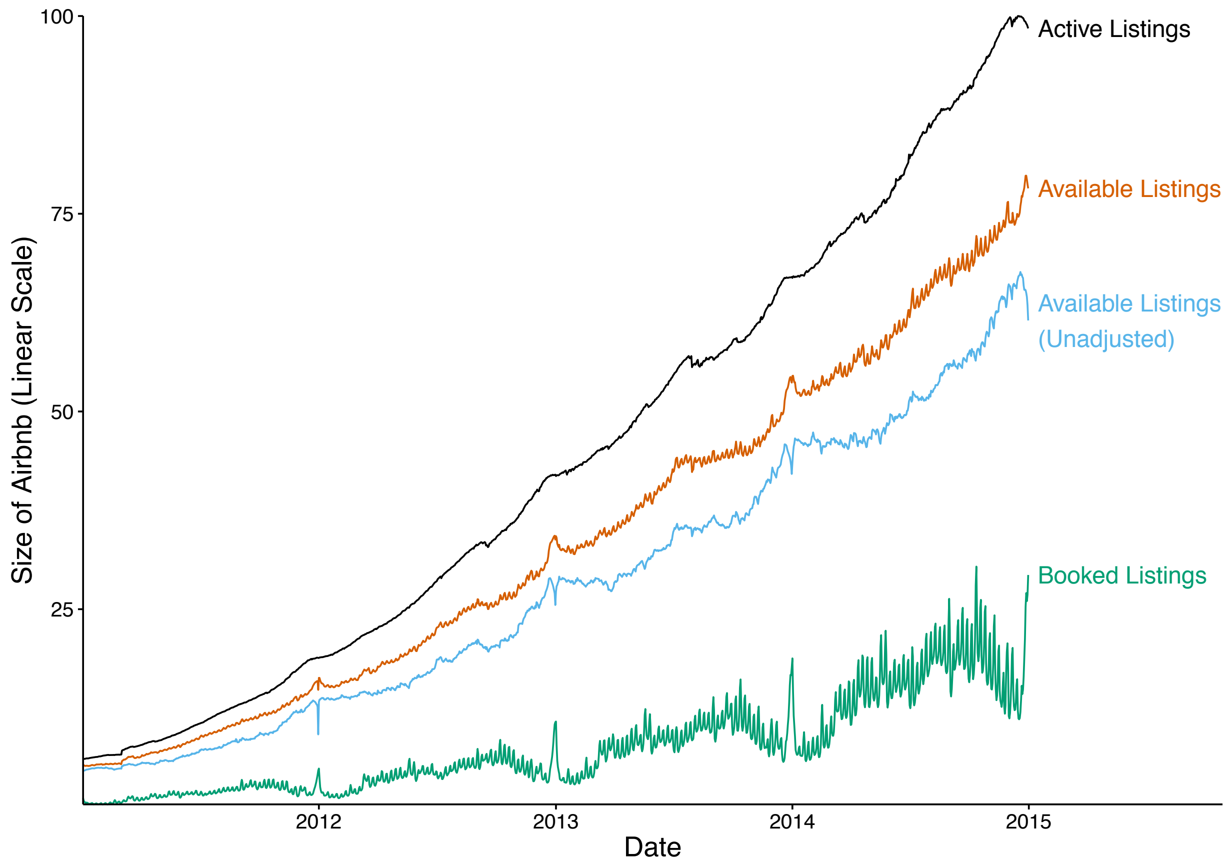
Figure 5: Peer Production and Demand Characteristics

(a) Demand Growth (b) Demand Variability



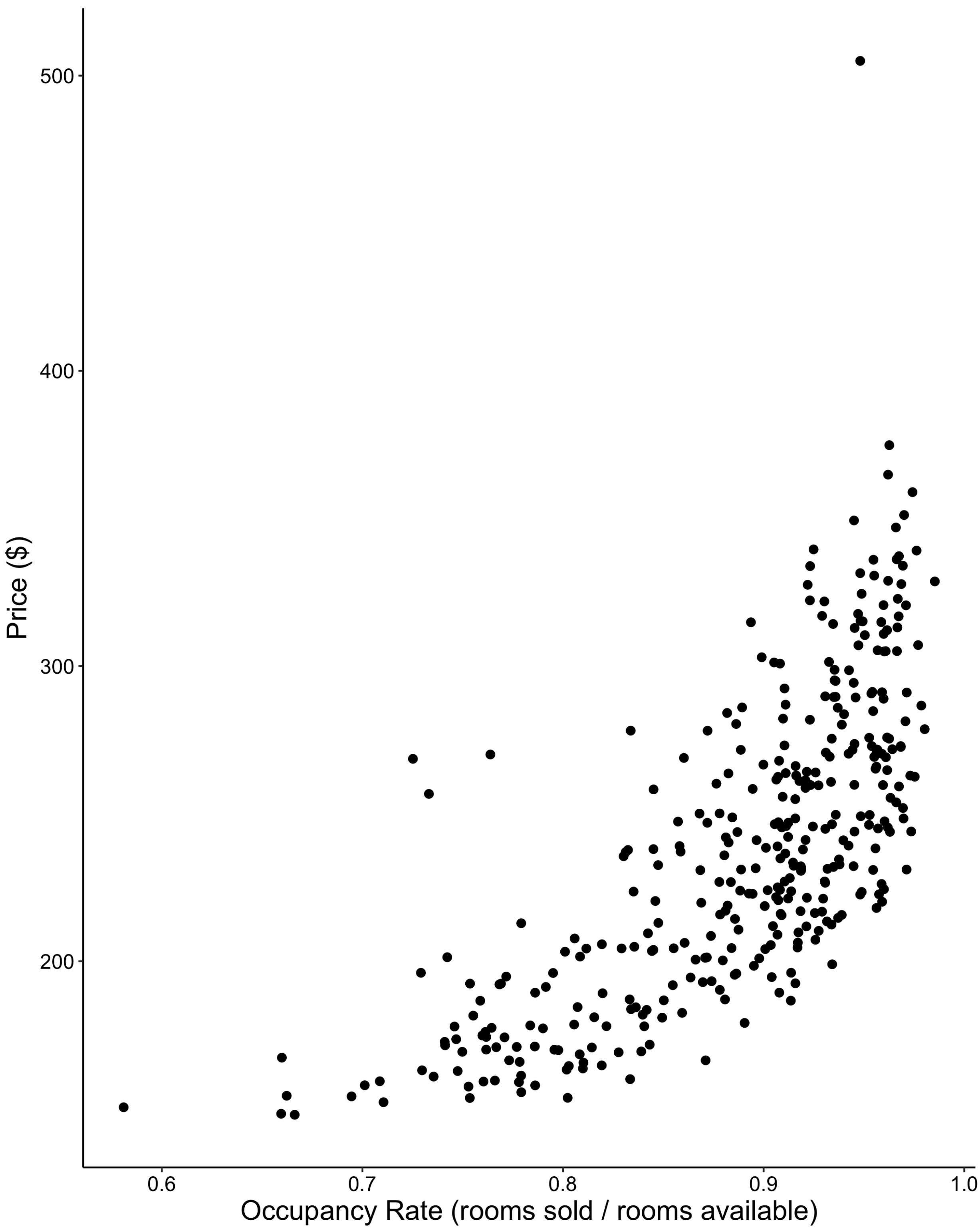

*The figures plot the size of Airbnb against the growth rate in incoming air passengers to an MSA between June 2011 and June 2012 (left) and against the standard deviation of incoming air passengers (right). The standard deviation of air travelers is measured using 2011 monthly data on arriving (not returning) passengers at major US airports. We focus on data from 2011-2012, when Airbnb was very small relative to the accommodation market, to limit the possibility that the availability of Airbnb hosts could generate such growth or variability in demand. The size of Airbnb is measured as the average share of available listings in the last quarter of 2014.*

Figure 6: Measures of Airbnb Supply: Demand-induced Calendar Updates



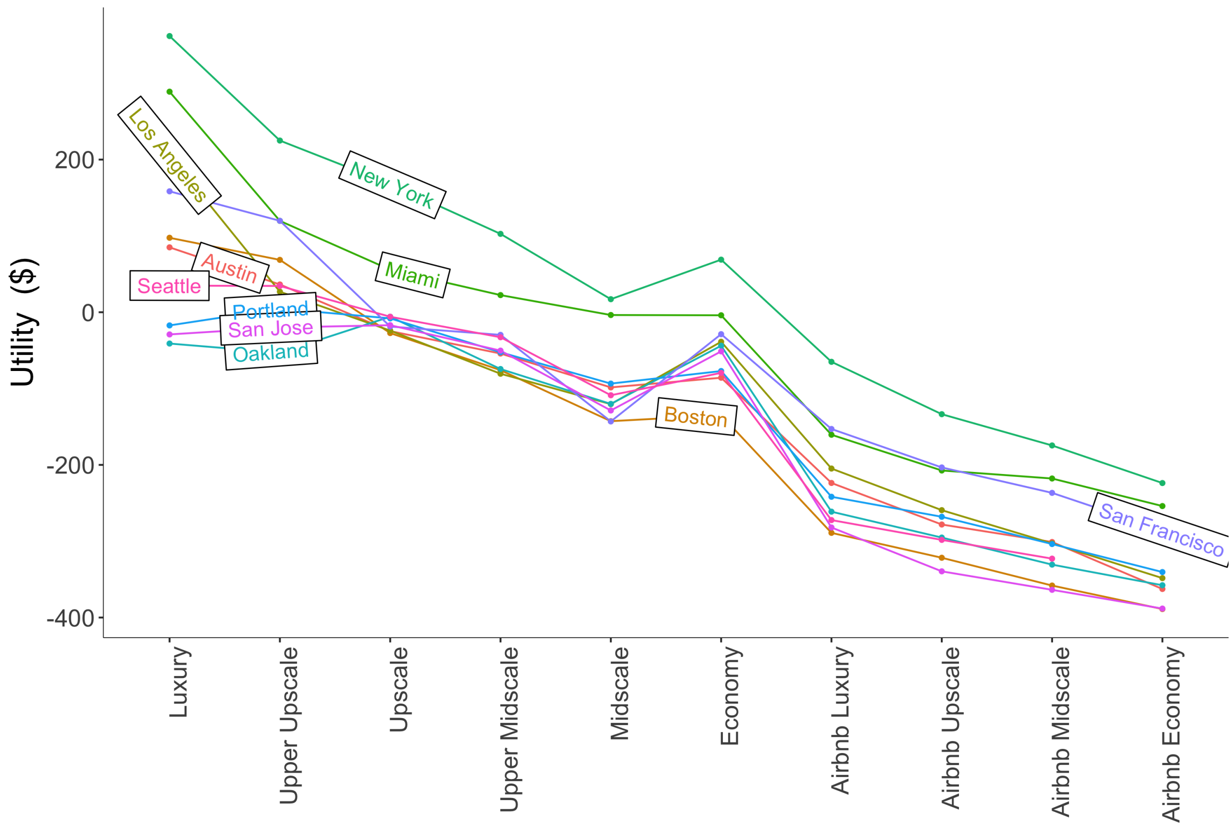

*This figure plots four measures of the size of Airbnb. An active listings is defined as a listing available to be booked or booked for any future date. An (unadjusted) available listing is one that is either booked or has an open calendar slot on the date of stay. Available listings augment the unadjusted measure with listings that were contacted and updated their calendars to be unavailable prior to the date of stay. A booked listing is one that has been booked for that date.*

Figure 7: Prices and Occupancy Rates




*This figure plots prices and occupancy rates of upscale hotels in New York in 2014.*

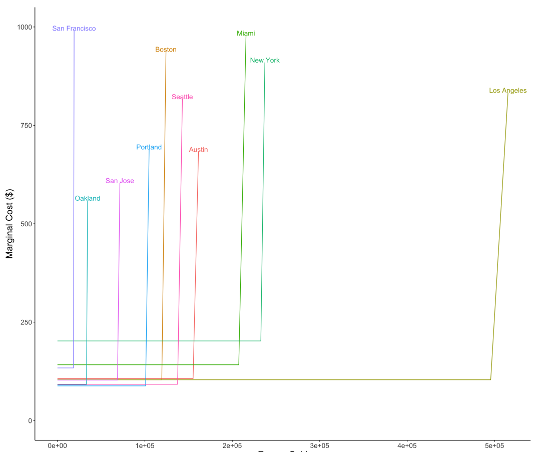
Figure 8: Estimated Utilities for Accommodation Options Across Cities



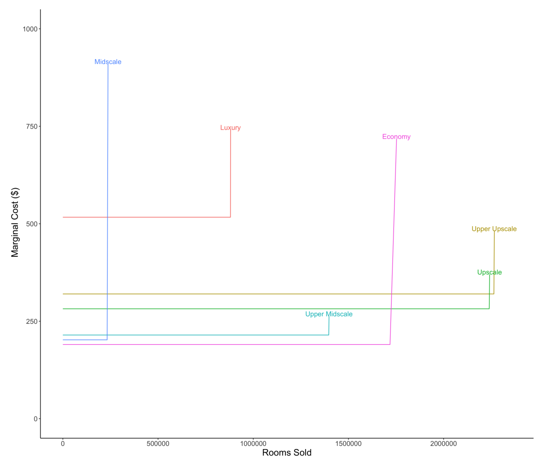

*This figure plots the estimated mean utilities for accommodation options across the 10 cities used in our estimation. The values are computed as averages over the last month in our data. The negative values of some of the parameters reflect the fact that our normalization of the outside option means that most people choose the outside option.*

Figure 9: Estimated Hotel Costs

(a) Costs by City – Midscale Hotels

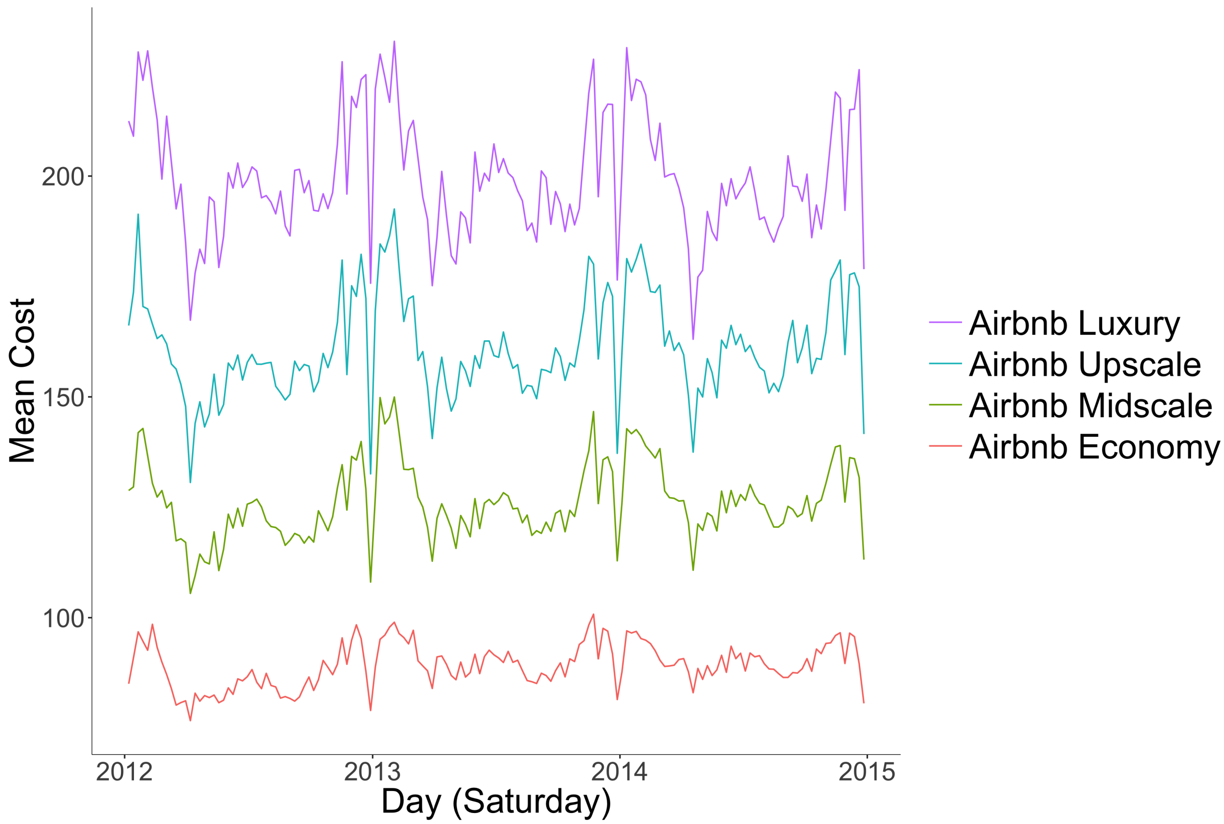



(b) Costs by Hotel Scale – New York City




*This figure plots the estimated marginal cost curves of hotels across cities (left panel) and across scales (right panel). The values are computed as averages over the last month in our data. Appendix Tables A6 and A7 display the cost estimates by city and hotel scale.*

Figure 10: Mean Costs of Airbnb Hosts in New York City




*The figures plot the estimated mean costs of Airbnb hosts in New York over time.*

# Tables

Table 1: Descriptive Statistics on Hotel and Airbnb Outcomes

| Statistic | N | Mean | St. Dev. | Pctl(25) | Median | Pctl(75) |
|---|---|---|---|---|---|---|
| Mean Hotel Occupancy | 50 | 0.66 | 0.07 | 0.61 | 0.65 | 0.70 |
| Std Dev Hotel Occupancy | 50 | 0.13 | 0.03 | 0.12 | 0.14 | 0.15 |
| Mean Hotel Price in $ | 50 | 107.94 | 35.04 | 86.29 | 98.69 | 121.01 |
| Std Dev Hotel Price | 50 | 16.34 | 9.34 | 9.77 | 13.00 | 21.02 |
| Mean Hotel Revenue (Thousand $) | 50 | 3,785.34 | 3,588.86 | 1,575.12 | 2,488.65 | 4,856.56 |
| Airbnb Share of Available Rooms (Q4 2014) | 50 | 0.02 | 0.03 | 0.005 | 0.01 | 0.03 |
| Airbnb Share of Potential Guests (Q4 2014) | 50 | 0.04 | 0.04 | 0.01 | 0.02 | 0.05 |
| Airbnb Share of Housing Units (Q4 2014) | 50 | 0.001 | 0.001 | 0.0002 | 0.0005 | 0.001 |
| Mean Airbnb Occupancy | 50 | 0.15 | 0.06 | 0.11 | 0.13 | 0.18 |
| Std Dev Airbnb Occupancy | 50 | 0.09 | 0.02 | 0.07 | 0.08 | 0.10 |
| Mean Airbnb Price in $ | 50 | 108.63 | 24.67 | 92.01 | 99.76 | 120.87 |
| Std Dev Airbnb Price | 50 | 31.24 | 13.17 | 21.78 | 28.50 | 34.29 |
| Mean Airbnb to Hotel Price Ratio | 50 | 1.06 | 0.28 | 0.91 | 1.00 | 1.14 |
| Std Dev Price Ratio | 50 | 0.33 | 0.18 | 0.21 | 0.29 | 0.39 |

*This table shows hotel and Airbnb descriptive statistics for the 50 cities in our sample. For each city, we compute the mean and standard deviation of daily occupancy rate and price for hotels and Airbnb listings. The Airbnb share of available rooms is computed as the average of daily share of rooms in the last quarter, i.e. October - December 2014. The Airbnb share of potential guests is computed as the quarterly average of rooms adjusted for their realized capacity, assuming that the typical hotel has the same number of average guests as a 'Midscale' Airbnb listing. This number is larger than the Airbnb share of rooms because Airbnb listings typically have higher capacity than hotel rooms.*

Table 2: Descriptive Statistics on Market Characteristics

| Statistic | N | Mean | St. Dev. | Pctl(25) | Median | Pctl(75) |
|---|---|---|---|---|---|---|
| WRLURI | 50 | 0.31 | 0.82 | −0.30 | 0.20 | 0.84 |
| Share of Undevelopable Area | 46 | 0.30 | 0.24 | 0.09 | 0.23 | 0.43 |
| Percent Never Married | 48 | 0.33 | 0.03 | 0.31 | 0.33 | 0.36 |
| Share of Children | 48 | 0.31 | 0.02 | 0.30 | 0.31 | 0.32 |
| Rent to Income Ratio | 50 | 0.18 | 0.03 | 0.15 | 0.17 | 0.20 |
| Std Dev of Google Trend (2011) | 50 | 12.05 | 4.22 | 9.62 | 11.51 | 13.70 |
| Std Dev of Incoming Passengers (2011) / 10,000 | 50 | 6.95 | 6.63 | 1.89 | 4.17 | 11.30 |
| Passengers' Growth (2012-2011) | 50 | 0.02 | 0.06 | −0.02 | 0.01 | 0.04 |

*The table shows descriptive statistics on market characteristics for the 50 cities in our sample. The WRLURI and Saiz's share of undevelopable area are proxies for constraints to hotel supply. The share of children and unmarried adults proxy for the availability of Airbnb hosts. The standard deviation of Google trends and incoming passengers are two measures of demand volatility.*

Table 3: City Characteristics and Size of Airbnb

| | Airbnb Share of Rooms | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Undevelopable Area | 0.025 | 0.021 | 0.013 |
| | (0.016) | (0.015) | (0.013) |
| SD. Incoming Air Passengers (2011) | 0.002*** | 0.002** | 0.0003 |
| | (0.001) | (0.001) | (0.001) |
| % Never Married | 0.364** | 0.391*** | 0.214 |
| | (0.140) | (0.144) | (0.131) |
| % Growth in Air Passengers (2012-2011) | 0.064 | 0.089 | 0.074 |
| | (0.058) | (0.058) | (0.050) |
| Wharton Residential Land Use Index (WRLURI) | | 0.006 | 0.004 |
| | | (0.004) | (0.003) |
| % Children | | −0.323* | −0.165 |
| | | (0.177) | (0.156) |
| Log(Market Size) | −0.011 | −0.007 | −0.010 |
| | (0.007) | (0.007) | (0.006) |
| Log(Rev. Per Room (2011)) | | | 0.055*** |
| | | | (0.014) |
| Constant | 0.001 | 0.051 | −0.120 |
| | (0.080) | (0.079) | (0.081) |
| Observations | 46 | 46 | 46 |
| $R^2$ | 0.584 | 0.644 | 0.748 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | | |

*This table shows linear regressions of the size of Airbnb on market characteristics linked to supply constraints, demand volatility, and the costs of hosting. The size of Airbnb is the average of daily share of rooms in the last quarter, i.e. October - December 2014. The standard deviation of incoming passengers is divided by 10,000 to make the coefficient comparable to the other variables. Descriptive statistics are shown in Tables 1 and 2. Market size is measured as the average number of rooms available in the last quarter of 2014.*

Table 4: The Supply Elasticity of Hotels and Peer Hosts

| | Log(Hotel Rooms Boooked) | Log(Airbnb Rooms Booked) |
|---|---|---|
| | (1) | (2) |
| log(Hotel Rooms) | 0.538*** | |
| | (0.188) | |
| log(Hotel Price) | 1.072*** | |
| | (0.069) | |
| log(Airbnb Rooms) | | 0.622*** |
| | | (0.098) |
| log(Airbnb Price) | | 2.164*** |
| | | (0.296) |
| IV | Yes | Yes |
| City FE | Yes | Yes |
| Year-Month FE | Yes | Yes |
| Day of Week FE | Yes | Yes |
| Observations | 268,489 | 250,923 |
| $R^2$ | 0.963 | 0.895 |

*Note:* Column 2 includes the log number of residents leaving by air, and the log number of outgoing travel searches on Google as controls. Standard Errors are clustered at the city and year-month level.

*The table shows results of IV regressions of the log of hotel and Airbnb bookings on the corresponding price and room availability. Column 2 includes the log of departing (local) air travelers, and the one week lag of the log of local Google Search Trends for hotels outside of the city as additional controls. The instruments are demand-side shifters – the one week lag of the log of the Google Search Trends and the log of arriving (not returning) flight travelers – in both columns. In column 2 the number of Airbnb available listings is instrumented with city-specific quadratic time trends that capture the diffusion process of the platform. Adding the city-day observations with no Airbnb bookings (and using hotel prices in column 2) does not change the results. Instrumenting for hotel capacity like we do for Airbnb does not change the results either.*

Table 5: Hotel Revenue and the Size of Airbnb

| | Log(RevPAR) | Occupancy Rate | Log(Price) |
|---|---|---|---|
| | (1) | (2) | (3) |
| log(Incoming Air Passengers) | 1.169*** | 0.394*** | 0.498*** |
| | (0.065) | (0.041) | (0.041) |
| log(Google Search Trend) | 0.147*** | 0.054*** | 0.069** |
| | (0.049) | (0.012) | (0.027) |
| log(Hotel Rooms) | −0.768*** | −0.436*** | −0.078 |
| | (0.200) | (0.078) | (0.148) |
| log(Available Listings) | −0.033** | −0.006 | −0.025* |
| | (0.014) | (0.005) | (0.013) |
| IV | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes |
| Day of Week FE | Yes | Yes | Yes |
| Observations | 268,489 | 268,489 | 268,489 |
| $R^2$ | 0.729 | 0.582 | 0.853 |
| *Note:* | Standard Errors Clustered at a City Level | | |

*This table shows results of IV estimates of equation 4, where the size of Airbnb is measured as the number of available listings. The Google search trend is a one-week lag. The instruments are city-specific quadratic time trends. The dependent variable is revenue per available room in column 1, occupancy rate in column 2, and price in column 3. Appendix B discusses the instrumental variables strategy and endogeneity concerns in greater detail.*

Table 6: Heterogeneous Effects of Airbnb: Market Supply Elasticity

| | Log(RevPAR) | Occupancy Rate | Log(Price) | Log(RevPAR) | Occupancy Rate | Log(Price) |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| log(Incoming Air Passengers) | 1.138*** | 0.411*** | 0.528*** | 1.283*** | 0.497*** | 0.440*** |
| | (0.110) | (0.031) | (0.069) | (0.128) | (0.034) | (0.082) |
| log(Google Search Trend) | 0.151* | 0.043** | 0.081* | 0.117 | 0.066** | 0.026 |
| | (0.091) | (0.021) | (0.047) | (0.072) | (0.026) | (0.026) |
| log(Hotel Rooms) | −0.717 | −0.359*** | −0.271 | −0.992** | −0.542*** | −0.002 |
| | (0.470) | (0.067) | (0.388) | (0.389) | (0.173) | (0.211) |
| log(Available Listings) | −0.070 | −0.009 | −0.060** | −0.006 | −0.007 | 0.008 |
| | (0.049) | (0.007) | (0.028) | (0.055) | (0.020) | (0.024) |
| City Type | Inelastic Housing Supply | | | Elastic Housing Supply | | |
| Instruments | Yes | Yes | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Day of Week FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 112,348 | 112,348 | 112,348 | 134,801 | 134,801 | 134,801 |
| $R^2$ | 0.741 | 0.597 | 0.852 | 0.547 | 0.507 | 0.701 |
| *Note:* | Standard Errors Clustered at a City and Year-Quarter Level | | | | | |

*The table shows results of IV estimates similar to Table 5, but we split the cities by the housing supply elasticity estimated in Saiz (2010). Inelastic cities are those with a housing supply elasticity below the median across our sample.*

## Table 7: Selected Estimated Parameters

| Parameter | Value | Std. Error |
|---|---|---|
| Price | -0.014 | 0.003 |
| Time Trend | 0.002 | 0.001 |
| Time Trend * Airbnb | 0.010 | 0.001 |
| Log Google Trend | 2.952 | 2.161 |
| Log Google Trend Sq. | -0.175 | 0.248 |
| Log Travelers To | 5.563 | 0.615 |
| Log Travelers To Sq. | -0.150 | 0.000 |
| Std. Deviation on Inside Option | 1.074 | 0.396 |
| Std. Deviation on Hotel Class | 0.354 | 0.223 |

*This table displays the estimated parameters and their standard errors for selected parameters in the model.*

Table 8: Consumer Surplus from Airbnb

| City | Change in CS (MM) | |
|---|---|---|
| | Unconstrained | Price Adjustment |
| Austin | -10.9 | -14.6 |
| Boston | -9.5 | -12.9 |
| Los Angeles | -56.5 | -67.4 |
| Miami | -18.8 | -23.6 |
| New York | -131.2 | -206.6 |
| Oakland | -8.3 | -10.0 |
| Portland | -11.7 | -14.1 |
| San Francisco | -46.5 | -67.4 |
| San Jose | -5.2 | -6.0 |
| Seattle | -7.3 | -9.6 |
| All | -305.9 | -432.0 |
| All (Compression Nights) | -80.8 | -138.4 |

*This table displays the consumer surplus from all accommodations in the baseline scenario and the gains from the Airbnb option for three scenarios. All calculations are for 2014. "Unconstrained" refers to the counterfactual scenario in which the Airbnb option does not exist and hotels can absorb the additional consumers regardless of their actual capacity, and "Price Adjustment" allows hotels to adjust prices in response to no longer having to compete with Airbnb. "All" refers to the sum across all cities, and "All (Compression Nights)" refers to the sum across cities for time periods when the hotel sector in the city had an occupancy of at least 95%.*

Table 9: Consumer Surplus from Airbnb (per night)

| City | Avg. Airbnb Price | Consumer Surplus per Person-Night | |
|---|---|---|---|
| | | Unconstrained | Price Adjustment |
| Austin | 160.6 | -52.8 | -70.7 |
| Boston | 136.2 | -60.8 | -82.3 |
| Los Angeles | 124.6 | -55.3 | -66.0 |
| Miami | 155.0 | -61.1 | -76.5 |
| New York | 145.3 | -43.8 | -68.9 |
| Oakland | 89.4 | -60.2 | -72.7 |
| Portland | 99.4 | -64.9 | -78.2 |
| San Francisco | 146.6 | -47.1 | -68.1 |
| San Jose | 113.4 | -63.6 | -73.8 |
| Seattle | 120.0 | -66.3 | -86.3 |
| All | 139.4 | -49.4 | -69.8 |
| All (Compression Nights) | 147.1 | -50.0 | -85.6 |

*This table displays the consumer surplus per night booked from the Airbnb option for three counterfactual scenarios. All calculations are for 2014. "Unconstrained" refers to the counterfactual scenario in which the Airbnb option does not exist and hotels can absorb the additional consumers regardless of their actual capacity, and "Price Adjustment" allows hotels to adjust prices in response to no longer having to compete with Airbnb. "All" refers to the sum across all cities, and "All (Compression Nights)" refers to the sum across cities for time periods when the hotel sector in the city had an occupancy of at least 95%.*

Table 10: Competitive Effects on Hotels

| City | % Change Quantity | | % Change Revenue | | % Change Profit | |
|---|---|---|---|---|---|---|
| | Unconst. | Price Adj. | Unconst. | Price Adj. | Unconst. | Price Adj. |
| Austin | 0.68 | 0.43 | 0.89 | 0.75 | 1.34 | 1.96 |
| Boston | 0.36 | 0.21 | 0.40 | 0.31 | 0.51 | 0.77 |
| Los Angeles | 1.03 | 0.77 | 1.18 | 1.01 | 1.51 | 4.40 |
| Miami | 0.71 | 0.50 | 0.84 | 0.70 | 1.15 | 1.22 |
| New York | 2.22 | 0.75 | 2.45 | 1.50 | 2.67 | 4.09 |
| Oakland | 0.74 | 0.54 | 0.81 | 0.77 | 0.96 | 2.71 |
| Portland | 0.85 | 0.63 | 0.95 | 0.88 | 1.24 | 3.01 |
| San Francisco | 1.59 | 0.72 | 1.73 | 1.23 | 1.82 | 4.04 |
| San Jose | 0.27 | 0.22 | 0.28 | 0.26 | 0.28 | 0.65 |
| Seattle | 0.33 | 0.21 | 0.38 | 0.32 | 0.52 | 1.05 |
| All | 1.12 | 0.57 | 1.44 | 1.00 | 1.81 | 3.05 |
| All (Compression) | 1.40 | 0.30 | 1.76 | 0.97 | 1.91 | 2.50 |

*This table displays hotel bookings and revenue across counterfactual scenarios. All calculations are for 2014. "Base" refers to the actual data, "Unconst." refers to the counterfactual scenario in which the Airbnb option does not exist and hotels can absorb the additional consumers regardless of their actual capacity, and "Price Adj." refers to the counterfactual where hotels adjust prices in response to no longer having to compete with Airbnb. Row "All" refers to the sum across all cities, and row "All (Compression)" refers to the sum across cities for time periods when the hotel sector in the city had an occupancy of at least 95%.*

Table 11: Airbnb Bookings: Market Expansion versus Business Stealing

| | Share New Bookings | |
|---|---|---|
| | Unconstr. | Price Adjust. |
| Austin | 0.62 | 0.76 |
| Boston | 0.61 | 0.78 |
| Los Angeles | 0.62 | 0.72 |
| Miami | 0.61 | 0.72 |
| New York | 0.59 | 0.86 |
| Oakland | 0.64 | 0.74 |
| Portland | 0.63 | 0.73 |
| San Francisco | 0.60 | 0.82 |
| San Jose | 0.64 | 0.71 |
| Seattle | 0.63 | 0.77 |

*This table shows the number of rooms booked on Airbnb by city and year according to our model estimates. "Unconstr." refers to the counterfactual scenario in which the Airbnb option does not exist and hotels can absorb the additional consumers regardless of their actual capacity, "Cap Constr." imposes hotel capacity constraints, and "Price Adjust." reflects the counterfactual where Airbnb is removed and hotels adjust prices.*

Table 12: Peer Producer Surplus

| City | Avg. Peer Surplus per Night | Total Peer Surplus (MM) |
|---|---|---|
| Austin | 30.86 | 1.17 |
| Boston | 26.87 | 0.99 |
| Los Angeles | 25.99 | 3.30 |
| Miami | 24.36 | 1.10 |
| New York | 28.07 | 7.90 |
| Oakland | 25.50 | 0.50 |
| Portland | 28.65 | 0.95 |
| San Francisco | 28.79 | 2.90 |
| San Jose | 27.47 | 0.52 |
| Seattle | 27.58 | 0.90 |
| All | 27.58 | 20.23 |
| All (Compression Nights) | 28.82 | 8.98 |

*This table displays the peer producer surplus for 2014. Row "All" refers to the sum across all cities, and row "All (Compression)" refers to the sum across cities for time periods when the hotel sector in the city had an occupancy of at least 95%.*

# A Appendix: Proof of Model Predictions

The short-run model from section 2.1 offers some comparative statics predictions. We present the propositions and the proofs below.

**Proposition 1** *Hotel profits and prices decrease in $K_a$. Hotel rooms sold decrease in $K_a$ if and only if* $-\frac{\partial Q_h}{\partial p_a}/\frac{\partial Q_h}{\partial p_h} \geq -\frac{\partial^2 \Pi_h}{\partial p_h \partial p_a}/\frac{\partial^2 \Pi_h}{\partial p_h^2}$.

Before we start the proof of Proposition 1 it is useful to separately consider markets where the hotel capacity constraint binds and markets where it does not. In markets where the hotel constraint binds the two equilibrium conditions are $Q_h(p_h, p_a) = K_h$ and $Q_a(p_a, p_h) = K_a G(p_a)$, where $G()$ denotes the distribution of flexible marginal costs. See Section 2.1 for details. By totally differentiating the system of equilibrium equations we find the total derivatives of hotel and Airbnb prices with respect to Airbnb capacity:

$$\left[\frac{dp_h}{dK_a}\right]^c = \frac{-\frac{\partial Q_h}{\partial p_a} G(p_a)}{\frac{\partial Q_h}{\partial p_h}\left[\frac{\partial Q_a}{\partial p_a} - K_a g(p_a)\right] - \frac{\partial Q_h}{\partial p_a}\frac{\partial Q_a}{\partial p_h}} \tag{A1}$$

$$\left[\frac{dp_a}{dK_a}\right]^c = \frac{\frac{\partial Q_h}{\partial p_h} G(p_a)}{\frac{\partial Q_h}{\partial p_h}\left[\frac{\partial Q_a}{\partial p_a} - K_a g(p_a)\right] - \frac{\partial Q_h}{\partial p_a}\frac{\partial Q_a}{\partial p_h}}. \tag{A2}$$

In markets where the hotel constraint does not bind the two equilibrium conditions are $\partial \Pi(p_a, p_h)/\partial p_h = 0$ and $Q_a(p_a, p_h) = K_a G(p_a)$. By totally differentiating the system of equilibrium equations we find the total derivatives of hotel and Airbnb prices with respect to Airbnb capacity:

$$\left[\frac{dp_h}{dK_a}\right]^u = \frac{-\frac{\partial^2 \Pi_h}{\partial p_h \partial p_a} G(p_a)}{\frac{\partial^2 \Pi_h}{\partial p_h^2}\left[\frac{\partial Q_a}{\partial p_a} - K_a g(p_a)\right] - \frac{\partial^2 \Pi_h}{\partial p_h \partial p_a}\frac{\partial Q_a}{\partial p_h}} \tag{A3}$$

$$\left[\frac{dp_a}{dK_a}\right]^u = \frac{\frac{\partial^2 \Pi_h}{\partial p_h^2} G(p_a)}{\frac{\partial^2 \Pi_h}{\partial p_h^2}\left[\frac{\partial Q_a}{\partial p_a} - K_a g(p_a)\right] - \frac{\partial^2 \Pi_h}{\partial p_h \partial p_a}\frac{\partial Q_a}{\partial p_h}}, \tag{A4}$$

where $\frac{\partial^2 \Pi_h}{\partial p_h^2} = 2\frac{\partial Q_h}{\partial p_h} + \frac{\partial^2 Q_h}{\partial p_h^2}(p_h - c_h)$, and $\frac{\partial^2 \Pi_h}{\partial p_h \partial p_a} = \left[\frac{\partial Q_h}{\partial p_a} + \frac{\partial^2 Q_h}{\partial p_h \partial p_a}(p_h - c_h)\right]$.

We start by proving that hotel prices are a decreasing function of flexible capacity in both constrained and unconstrained equilibria. To do that, we need to prove that the derivatives in equation A1 and A3 are negative. $\left[\frac{dp_h}{dK_a}\right]^c \leq 0$ since the numerator is negative and the denominator is positive. The numerator is negative as long as hotels and Airbnb rooms are substitutes, or $\frac{\partial Q_h}{\partial p_a} \geq 0$. The denominator is positive because the first term is the product of two negative terms, and the second term to be substracted is positive but smaller than the first term in absolute value. Indeed, $-\frac{\partial Q_a}{\partial p_a} + K_a g(p_a) \geq \frac{\partial Q_h}{\partial p_a} \geq 0$ and $-\frac{\partial Q_h}{\partial p_h} \geq \frac{\partial Q_a}{\partial p_h}$ since own-price elasticities are negative, cross-price elasticities are positive, and as long as there is an outside good with positive demand $Q_0$, $-\frac{\partial Q_j}{\partial p_j} = \frac{\partial Q_i}{\partial p_j} + \frac{\partial Q_0}{\partial p_j} \geq \frac{\partial Q_i}{\partial p_j}$.

A similar reasoning proves that $\left[\frac{dp_h}{dK_a}\right]^u \leq 0$. The inequality holds as long as the Bertrand price equilibrium is stable and hotel optimal prices are an increasing function of competitors' prices (Bulow et al. (1985)). The conditions on the stability of equilibrium and strategic complementarity in prices imply that $-\frac{\partial^2 \Pi_h}{\partial p_h^2} \geq \frac{\partial^2 \Pi_h}{\partial p_h \partial p_a} \geq 0$ , or $-\left[2\frac{\partial Q_h}{\partial p_h} + \frac{\partial^2 Q_h}{\partial p_h^2}(p_h - c_h)\right] \geq \left[\frac{\partial Q_h}{\partial p_a} + \frac{\partial^2 Q_h}{\partial p_h \partial p_a}(p_h - c_h)\right] \geq 0$.

So far, we have proved that an increase in flexible capacity decreases hotel prices by showing that $\frac{dp_h}{dK_a} \leq 0$ whether or not the hotel is operating at capacity.

Now we prove that an increase in flexible capacity also decreases hotel profits in both constrained and unconstrained equilibria. An increase in $K_a$ affects hotel profits $\Pi_h = Q_h^d(p_h - c_h)$ through changes in $p_a$ and $p_h$:

$$\frac{d\Pi_h}{dK_a} = \frac{\partial \Pi_h}{\partial p_h}\frac{dp_h}{dK_a} + \frac{\partial \Pi_h}{\partial p_a}\frac{dp_a}{dK_a}. \tag{A5}$$

Let us first consider the case where the hotel capacity constraint binds, and the price derivatives with respect to $K_a$ are given by equations A1 and A2. Since we are at a constrained maximum $\frac{\partial \Pi_h}{\partial p_h} = \frac{\partial Q_h}{\partial p_h}(p_h - c_h) + Q_h < 0$. Since hotel and Airbnb rooms are substitutes $\frac{\partial \Pi_h}{\partial p_a} = \frac{\partial Q_h}{\partial p_a}(p_h - c_h) \geq 0$. After substituting the expressions of $\frac{\partial \Pi_h}{\partial p_h}$ and $\frac{\partial \Pi_h}{\partial p_a}$, and equations A1 and A2 into equation A5, simple algebra shows that equation A5 is negative if and only if $-Q_h \frac{\partial Q_h}{\partial p_a} G(p_a) \leq 0$, which is always true.

Let us now consider the case where the hotel capacity constraint does not bind. At the unconstrained optimum the first order condition holds with equality, $\frac{\partial \Pi_h}{\partial p_h} = 0$, so the first term in equation A5 is zero. The second term has the same sign as $\left[\frac{dp_a}{dK_a}\right]^u \leq 0$. From equation A4, this derivative is negative because it has the same sign as $\frac{\partial^2 \Pi_h}{\partial p_h^2}$. The last expression is the second derivative of the hotel profit optimization function, which is negative for an interior maximum. Combining these results implies that flexible prices are a decreasing function of flexible capacity even when hotels are not capacity constrained in equilibrium. Therefore, whether the hotel is operating at capacity or not, $\frac{d\Pi_h}{dK_a} \leq 0$: an increase in flexible capacity reduces hotel profits.

We are left with proving that hotel rooms sold decrease in $K_a$ if and only if $-\frac{\partial Q_h}{\partial p_a} / \frac{\partial Q_h}{\partial p_h} \geq -\frac{\partial^2 \Pi_h}{\partial p_h \partial p_a} / \frac{\partial^2 \Pi_h}{\partial p_h^2}$. In words, this condition requires that the hotel best response function to competitor prices is steeper when hotel occupancy is held fixed than when hotel occupancy is allowed to change.[16] The total derivative of hotel rooms sold with respect to Airbnb capacity is equal to

$$\frac{dQ_h}{dK_a} = \frac{\partial Q_h}{\partial p_h}\frac{dp_h}{dK_a} + \frac{\partial Q_h}{\partial p_a}\frac{dp_a}{dK_a}. \tag{A6}$$

When hotels are operating at capacity a marginal change in Airbnb capacity does not change hotel occupancy. Indeed, substituting equations A1 and A2 gives $\left[\frac{dQ_h}{dK_a}\right]^c = 0$. When hotels are not operating at capacity, substituting equations A3 and A4 gives $\left[\frac{dQ_h}{dK_a}\right]^c = \frac{-\frac{\partial Q_h}{\partial p_h}\frac{\partial^2\Pi_h}{\partial p_h \partial p_a}G(p_a)+\frac{\partial Q_h}{\partial p_a}\frac{\partial^2\Pi_h}{\partial p_h^2}G(p_a)}{\frac{\partial^2\Pi_h}{\partial p_h^2}\left[\frac{\partial Q_a}{\partial p_a}-K_a g(p_a)\right]-\frac{\partial^2\Pi_h}{\partial p_h \partial p_a}\frac{\partial Q_a}{\partial p_h}}$. We have already proved that the denominator is positive, while the numerator is negative as long as $-\frac{\partial Q_h}{\partial p_h}\frac{\partial^2\Pi_h}{\partial p_h \partial p_a} + \frac{\partial Q_h}{\partial p_a}\frac{\partial^2\Pi_h}{\partial p_h^2} \leq 0$, which is identical to the condition stated in the proposition. ∎

**Proposition 2** *The reduction in hotel prices when flexible capacity increases is larger when hotel capacity constraints bind if and only if* $-\frac{\partial Q_h}{\partial p_a}/\frac{\partial Q_h}{\partial p_h} \geq -\frac{\partial^2\Pi_h}{\partial p_h \partial p_a}/\frac{\partial^2\Pi_h}{\partial p_h^2}$. *Under the same condition, the reduction in hotel rooms sold when flexible capacity increases is larger when hotel capacity constraints do not bind.*

To prove that hotel prices fall more as a function of flexible capacity when hotel capacity constraints bind, it suffices to show that equation A1 is smaller than equation A3. In proving proposition 1 we have showed that both derivatives are negative. After some algebra, the condition $\left[\frac{dp_h}{dK_a}\right]^c \leq \left[\frac{dp_h}{dK_a}\right]^u$ simplifies to $-\frac{\partial Q_h}{\partial p_a}/\frac{\partial Q_h}{\partial p_h} \geq -\frac{\partial^2\Pi_h}{\partial p_h \partial p_a}/\frac{\partial^2\Pi_h}{\partial p_h^2}$.

To prove that hotel rooms sold fall more as a function of flexible capacity when hotel capacity constraints do not bind, we again use parts of the proof of Proposition 1. There, we have showed that hotel rooms sold are unchanged following a marginal increase in flexible capacity whenever hotel constraints bind: $\left[\frac{dQ_h}{dK_a}\right]^c = 0$. We have also showed that $\left[\frac{dQ_h}{dK_a}\right]^u \leq 0$ if and only if $-\frac{\partial Q_h}{\partial p_a}/\frac{\partial Q_h}{\partial p_h} \geq -\frac{\partial^2\Pi_h}{\partial p_h \partial p_a}/\frac{\partial^2\Pi_h}{\partial p_h^2}$. Therefore $\left[\frac{dQ_h}{dK_a}\right]^u \leq \left[\frac{dQ_h}{dK_a}\right]^c$. ∎

The next proposition contains comparative statics results on the long-run entry of peer supply. Throughout, we assume that all flexible suppliers with joining costs lower than $\bar{C}$, where $\bar{C} = v_a = \int_d E_c\left(max\{0, p_a^d - c\}\right)dF(d)$ have already joined. This corresponds to mass $K_a$.

**Proposition 3** *Entry of flexible sellers is larger ($K_a$ increases) if the distribution of peers' marginal costs $c$ decreases in the sense of first-order stochastic dominance. $K_a$ increases*

[16] $-\frac{\partial Q_h}{\partial p_a}/\frac{\partial Q_h}{\partial p_h}$ is the partial derivative of hotel prices with respect to Airbnb prices computed by implicit function theorem on the constrained equilibrium condition, $Q_h(p_h, p_a) = K_h$. Analogously, $-\frac{\partial^2\Pi_h}{\partial p_h \partial p_a}/\frac{\partial^2\Pi_h}{\partial p_h^2}$ is the partial derivative under the unconstrained equilibrium condition, $\partial\Pi_h(p_h, p_a)/\partial p_h = 0$.

*if $K_h$ decreases. $K_a$ also increases if $F(d)$ increases in the sense of first order stochastic dominance or in response to a mean-preserving spread in $F(d)$.*

It is intuitive that if the distribution of flexible marginal costs $c$ shifts to the left, $E_c\left[max\{0, p_a^d - c\}\right]$ weakly increases in every demand state, so $v_a$ increases and more flexible sellers enter.

It is also straightforward to see that if $F(d)$ shifts to the right, $E_c\left[max\{0, p_a^d - c\}\right]$ will not change for any demand state, but higher demand states are more likely so $v_a$ increases, inducing more flexible entry.

Proving that a reduction in $K_h$ induces more flexible entry requires a little more explanation. Assume $K_h$ decreases on the margin. For demand states for which $K_h$ was not binding, the decrease in hotel capacity has no effect, so $p_a^d$ does not change for $d$ lower than a certain threshold. For demand states in which $K_h$ was binding the two equilibrium conditions are, with simplified notation, $Q_h^d(p_h, p_a) = K_h$ and $Q_a^d(p_a, p_h) = K_aG(p_a)$. We proved above (for Propositions 1 and 2) that an increase in flexible capacity decreases both hotel and peer prices. An analogous proof is valid for a change in hotel capacity. So for high demand states a decrease in hotel capacity increases flexible prices. So far we showed that in unconstrained demand states flexible prices do not change if $K_h$ decreases, while in constrained demand states they increase. This is a shift in the distribution of flexible prices in the sense of first order stochastic dominance. So $\frac{dv_a}{dK_h} \leq 0$ and a decrease in hotel capacity induces more flexible entry.

Finally, a mean-preserving spread of $F(d)$ induces more entry of flexible sellers. The utility function for demand state $d$, $E_c\left[max\{0, p_a^d - c\}\right]$, is a convex function of $p_a^d$. Since $p_a^d$ is an increasing function of $d$, as long as it is not too concave, the result is a direct implication of Jensen's inequality. Intuitively, flexible sellers lose nothing from low demand periods since they can choose not to host, and gain high profits in periods of high demand. A sufficient condition for this to hold is that flexible prices are non-decreasing in $d$, which is the case if hotel and flexible prices are strategic complements and the Bertrand price equilibrium is stable. As before, the proof relies on totally differentiating the system of equilibrium equations $Q_a^d = K_aG(p_a)$ and $Q_h^d = -\frac{\partial Q_h^d}{\partial p_h}(p_h - c_h)$ (which is $Q_h^d = K_h$ if hotels are capacity-constrained) with respect to the demand state and the price variables. The sufficient conditions require that $-\frac{\partial^2 \Pi_h^d}{\partial p_h \partial p_a} / \frac{\partial^2 \Pi_h^d}{\partial p_h^2} \in (0, 1)$ (equilibrium stability and strategic complementarity of hotel and flexible prices) and $-\frac{\partial^2 \Pi_h^d}{\partial p_h \partial d} / \frac{\partial^2 \Pi_h^d}{\partial p_h^2} \geq 0$ (optimal hotel price is an increasing function of demand), where ${\partial \Pi_h^d}/{\partial p_h}$ is the first order condition of the hotel maximization problem. ■

# B Appendix: Endogeneity Concerns

This Appendix presents evidence validating our baseline specification in equation 4 against endogeneity concerns. First, in Table A1 we progressively add controls from a simple regression of hotel revenue on the size of Airbnb. Our baseline specification in OLS form is in the fifth column. The coefficients of Airbnb listings decreases as we keep adding controls for demand fluctuations, days of the weeks, seasonality, and market-specific characteristics.

Appendix Table A2 displays OLS results using specification 4 for four different measures of Airbnb size: active, available (the naive version), adjusted available, and booked Airbnb rooms. This table shows the flaws related to each potential measure of Airbnb size. A regression using active listings, displayed in Column (1), results in a negative, but small effect. Column (2) displays results using the naive measure of available listings. In this case, the OLS estimate is much larger in magnitude than our IV estimates. The reason for this, as previously described, is that this variable is counter-cyclical: hosts are more likely to update their unavailability on their calendar in periods of high demand, meaning that measured supply is negatively correlated with demand. Column (3) displays our preferred measure of availability described in the previous section. The OLS estimate is not significant and smaller in magnitude than the IV estimate, which is expected if there is bias due to the number of available listings being positively correlated with demand. Lastly, Column (4) shows the results with respect to the number of Airbnb bookings. There is a positive and statistically significant coefficient because demand for Airbnb is highest precisely in times of high overall accommodations demand, as shown in the previous subsection.

Appendix Table A3 displays the full set of results described in the previous paragraph but with the measure of Airbnb instrumented with city-specific quadratic time trends. Using this strategy, the effect of Airbnb is similar regardless of the measure used, except for booked listings.

Table A1: Hotel Revenue and Airbnb - Additional Controls

| | Log(Revenue per Available Hotel Room) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| log(Available Listings) | 0.177*** | 0.124*** | 0.125*** | 0.043*** | −0.032 |
| | (0.019) | (0.016) | (0.016) | (0.005) | (0.021) |
| log(Google Search Trend) | | 0.388*** | 0.388*** | 0.311*** | 0.147*** |
| | | (0.060) | (0.060) | (0.037) | (0.049) |
| log(Incoming Air Passengers) | | 0.181*** | 0.180*** | 1.016*** | 1.169*** |
| | | (0.041) | (0.041) | (0.047) | (0.065) |
| log(Hotel Rooms) | | −0.166* | −0.166* | −0.444* | −0.767*** |
| | | (0.099) | (0.099) | (0.254) | (0.198) |
| Day of Week FE | No | No | Yes | Yes | Yes |
| City FE | No | No | No | Yes | Yes |
| Quarter-Year FE | No | No | No | No | Yes |
| Observations | 268,489 | 268,489 | 268,489 | 268,489 | 268,489 |
| $R^2$ | 0.325 | 0.445 | 0.504 | 0.717 | 0.729 |

*Note:* Standard Errors Clustered at a City Level

*The table shows OLS estimates of equation 4. It progressively add controls: day of the week fixed effects, month fixed effects (January 2011 is a different fixed effect from January 2012), market fixed effects (e.g. SF), and city-specific time trends. The first columns show clearly a spurious correlation: Airbnb grows in markets where the accommodation industry is thriving. With the inclusion of additional controls the effect of Airbnb is negative across the markets under consideration.*

Table A2: Hotel Revenue and Airbnb - Different Measures of Airbnb

| | Log(Revenue per Available Hotel Room) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| log(Active Listings) | $-0.015$ | | | |
| | (0.013) | | | |
| log(Available Listings Raw) | | $-0.101^{***}$ | | |
| | | (0.027) | | |
| log(Available Listings Corrected) | | | $-0.032$ | |
| | | | (0.021) | |
| log(Booked Listings) | | | | $0.139^{***}$ |
| | | | | (0.013) |
| log(Google Search Trend) | $0.147^{***}$ | $0.145^{***}$ | $0.147^{***}$ | $0.122^{***}$ |
| | (0.050) | (0.049) | (0.049) | (0.047) |
| log(Incoming Air Passengers) | $1.171^{***}$ | $1.149^{***}$ | $1.169^{***}$ | $0.961^{***}$ |
| | (0.065) | (0.063) | (0.065) | (0.056) |
| log(Hotel Rooms) | $-0.758^{***}$ | $-0.783^{***}$ | $-0.767^{***}$ | $-0.651^{*}$ |
| | (0.193) | (0.270) | (0.198) | (0.349) |
| Day of Week FE | Yes | Yes | Yes | Yes |
| Quarter-Year FE | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes |
| Observations | 268,489 | 268,489 | 268,489 | 268,489 |
| $R^2$ | 0.729 | 0.731 | 0.729 | 0.744 |
| *Note:* | Standard Errors Clustered at a City Level | | | |

*The table shows results of OLS estimates of equation 4, where the size of Airbnb is measured as the number of active listings (column 1), the number of available listings adjusted for demand-induced calendar updates (column 2), the number of available listings (column 3), or the number of booked listings (column 4).*

Table A3: Hotel Revenue and Airbnb - IV Estimates for Different Measures of Airbnb

| | Log(Revenue per Available Hotel Room) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| log(Google Search Trend) | 0.148*** | 0.146*** | 0.147*** | 0.148*** |
| | (0.049) | (0.049) | (0.049) | (0.050) |
| log(Incoming Air Passengers) | 1.172*** | 1.163*** | 1.169*** | 1.189*** |
| | (0.065) | (0.065) | (0.065) | (0.071) |
| log(Hotel Rooms) | −0.766*** | −0.761*** | −0.768*** | −0.759*** |
| | (0.199) | (0.199) | (0.200) | (0.198) |
| log(Active Listings) | −0.034** | | | |
| | (0.014) | | | |
| log(Available Listings Raw) | | −0.034** | | |
| | | (0.014) | | |
| log(Available Listings Corrected) | | | −0.033** | |
| | | | (0.014) | |
| log(Booked Listings) | | | | −0.012 |
| | | | | (0.014) |
| Day of Week FE | Yes | Yes | Yes | Yes |
| Month-Year FE | Yes | Yes | Yes | Yes |
| Market FE | Yes | Yes | Yes | Yes |
| Observations | 268,489 | 268,489 | 268,489 | 268,489 |
| $R^2$ | 0.729 | 0.730 | 0.729 | 0.726 |
| *Note:* | Standard Errors Clustered at a City Level | | | |

*The table shows IV estimates of equation 4 for four different measures of Airbnb size from table A2: active listings, available listings adjusted for demand-induced calendar updates, available listings, and booked listings.*

# C Appendix: Additional Details and Results from the Structural Estimation

## C.1 Formulation of Differentiation Instruments

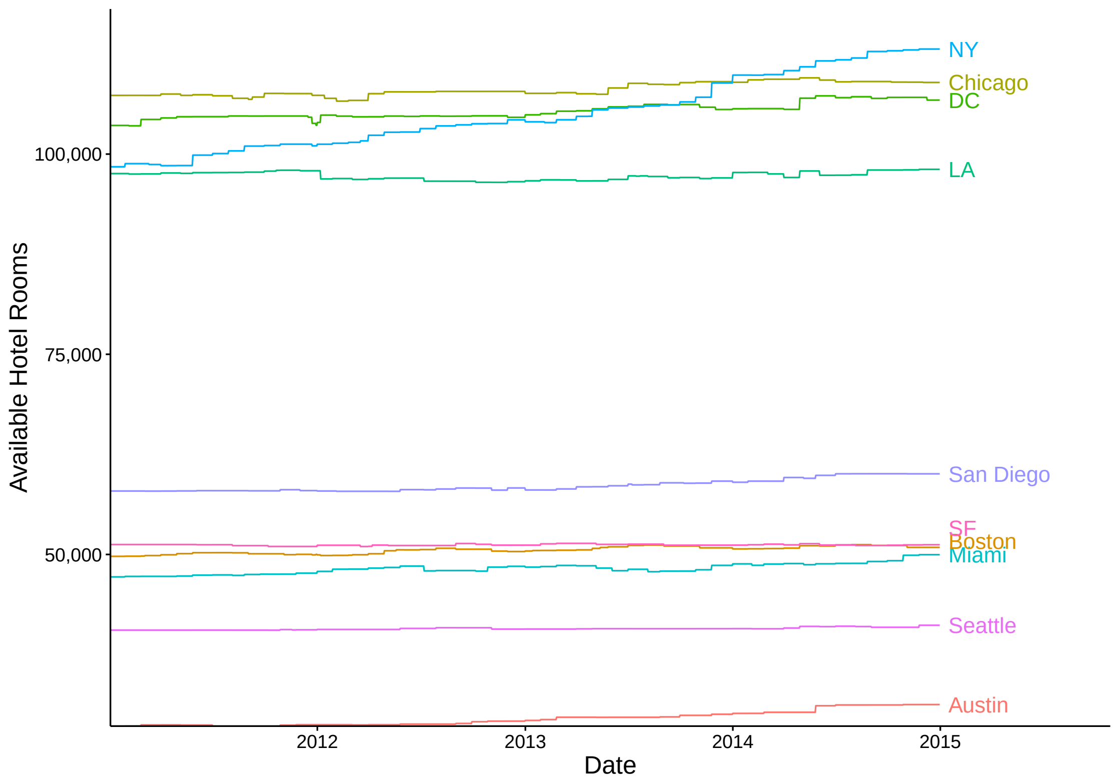
In this section, we describe the demand side differentiation instruments $IV$. The first step of formulating these instruments is to predict the after-tax price, $\hat{\hat{p}}_{jn} = (1+\tau_{jn})\hat{p}_{jn}$. We then use this price to derive measures of the amount of competition between options in a market $n$. The instruments used are:

- $IV_{1jn} = \sum_{i \neq j} \mathbb{1}\left(abs(\hat{\hat{p}}_{in} - \hat{\hat{p}}_{jn}) < std_{\hat{\hat{p}}_c}\right)$, where $std_{\hat{\hat{p}}_c}$ is the standard deviation of predicted prices over time within city $c$.
- $IV_{2jn} = \sum_{i=j-1} \hat{\hat{p}}_{in} - \hat{\hat{p}}_{jn}$. This is equal to zero for luxury hotels, and Airbnb highest quality tier.
- $IV_{3jn} = \sum_{i=j-1} (\hat{\hat{p}}_{in} - \hat{\hat{p}}_{jn})^2$. This is equal to zero for luxury hotels, and Airbnb highest quality tier.
- $IV_{4jn} = \sum_{i=j+1} \hat{\hat{p}}_{in} - \hat{\hat{p}}_{jn}$. This is equal to zero for economy hotels, and Airbnb lowest quality tier.
- $IV_{5jn} = \sum_{i=j+1} (\hat{\hat{p}}_{in} - \hat{\hat{p}}_{jn})^2$. This is equal to zero for economy hotels, and Airbnb lowest quality tier.
- $IV_{6jn} = \sum_{i \in \text{hotels}} \left(\hat{\hat{p}}_{in} - \hat{\hat{p}}_{jn}\right)$. This is equal to zero for Airbnb options.
- $IV_{7jn} = \sum_{i \in \text{hotels}} (\hat{\hat{p}}_{in} - \hat{\hat{p}}_{jn})^2$. This is equal to zero for Airbnb options.

We then do a principal component decomposition of $IV$, and keep the largest factors accounting for 99% of the variation.

## C.2 Additional Figures and Tables

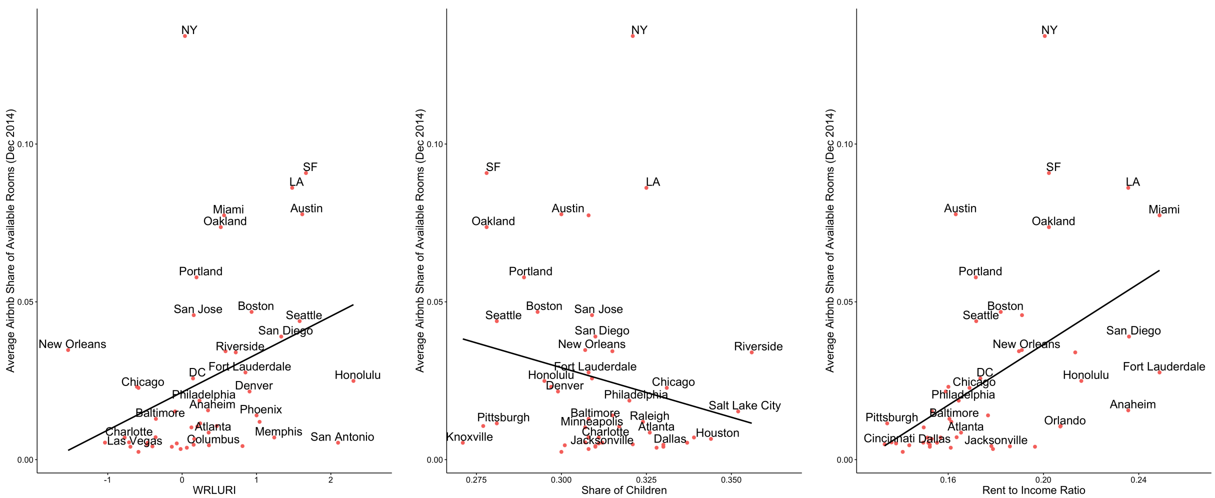
Figure A1: Hotel Rooms




*The figure plots the number of available hotel rooms over time for the top 10 cities. In contrast to the growth of Airbnb, the number of hotel rooms has been relatively stable over this time period.*

Figure A2: Peer Production and Supply Characteristics

(a) Regulatory Constrains (b) Share of Children (c) Housing Costs




*The figures are analogous to Figure 4a and Figure 4b. The left figure plots the size of Airbnb against a measure of constraints to the construction of new hotels: the Wharton Residential Land Use Regulation Index. The index measures how stringent the local regulatory environment is in the housing market, which we consider to be similar for commercial buildings. The center figure plots the size of Airbnb against the share of children in the MSA. The right figure plots the size of Airbnb against the ratio of median rent to household income in the MSA in 2010. The size of Airbnb is measured as the average share of available listings in the last quarter of 2014.*

Table A4: Heterogeneous Effects of Airbnb: Hotel Scale

| | Log(Price) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| log(Incoming Air Passengers) | 0.670*** | 0.543*** | 0.476*** | 0.444*** |
| | (0.076) | (0.066) | (0.065) | (0.057) |
| log(Google Search Trend) | 0.130** | 0.055 | 0.109** | 0.099** |
| | (0.059) | (0.043) | (0.043) | (0.040) |
| log(Hotel Rooms) | 0.294 | 0.034 | −0.280 | −0.872*** |
| | (0.580) | (0.290) | (0.228) | (0.332) |
| log(Available Listings) | 0.006 | −0.064** | −0.058* | −0.090*** |
| | (0.031) | (0.031) | (0.030) | (0.022) |
| Hotel Scale | Luxury | Upscale | Midscale | Economy |
| Instruments | City Time Trends | | | |
| City FE | Yes | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes | Yes |
| Day of Week FE | Yes | Yes | Yes | Yes |
| Observations | 90,863 | 112,348 | 112,348 | 112,348 |
| $R^2$ | 0.817 | 0.716 | 0.828 | 0.916 |
| *Note:* | Standard Errors Clustered at a City and Year-Quarter Level | | | |

*The table shows the IV estimates of equation 4 split by the type of hotel, where the size of Airbnb is measured as the number of available listings and Airbnb listings are instrumented by a city-specific quadratic time-trend. The Google search trend is a one-week lag. The instruments are city-specific quadratic time trends. The dependent variable is log price.*

Table A5: Own Price Elasticities by City and Accommodation Type

| | Austin | Boston | Los Angeles | Miami | New York | Oakland | Portland | San Francisco | San Jose | Seattle |
|---|---|---|---|---|---|---|---|---|---|---|
| Luxury | -5.01 | -4.66 | -5.31 | -4.75 | -6.18 | -3.05 | -2.85 | -4.25 | -2.63 | -3.41 |
| Upper Upscale | -2.55 | -2.37 | -2.02 | -2.71 | -3.67 | -1.62 | -2.12 | -2.49 | -1.82 | -2.26 |
| Upscale | -1.89 | -1.85 | -1.89 | -2.14 | -3.25 | -1.54 | -1.54 | -2.07 | -1.66 | -1.76 |
| Upper Midscale | -1.58 | -1.70 | -1.66 | -1.91 | -2.89 | -1.46 | -1.26 | -2.17 | -1.58 | -1.55 |
| Midscale | -1.44 | -1.55 | -1.45 | -1.90 | -2.86 | -1.30 | -1.18 | -2.07 | -1.57 | -1.38 |
| Economy | -0.75 | -1.14 | -0.87 | -1.41 | -2.35 | -0.79 | -0.78 | -1.48 | -1.00 | -0.88 |
| Airbnb Top | -2.13 | -1.91 | -2.04 | -2.53 | -2.33 | -1.34 | -1.44 | -2.14 | -1.55 | -1.66 |
| Airbnb Upper Mid | -1.76 | -1.67 | -1.65 | -2.00 | -1.97 | -1.21 | -1.32 | -2.00 | -1.38 | -1.54 |
| Airbnb Lower Mid | -1.48 | -1.36 | -1.40 | -1.78 | -1.61 | -1.08 | -1.12 | -1.71 | -1.22 | -1.30 |
| Airbnb Low | -1.13 | -0.83 | -1.03 | -1.37 | -1.15 | -0.86 | -0.95 | -1.30 | -0.92 | |

*This table displays the own-price elasticities of demand implied by our structural estimates, computed as averages at the city and accommodation type level. 'Airbnb Low' does not exist for Seattle because its supply share never exceeds 1%.*

## Table A6: Hotel Cost Estimates - Linear Component

| STR_name | Luxury | Upper Upscale | Upscale | Upper Midscale | Midscale | Economy |
|---|---|---|---|---|---|---|
| Austin/TX | 216.911 | 84.223 | 54.556 | 57.211 | 63.633 | 14.487 |
| Boston/MA | 209.613 | 113.135 | 91.648 | 73.833 | 60.993 | 54.714 |
| Los Angeles/Long Beach/CA | 285.218 | 107.220 | 92.024 | 76.089 | 65.438 | 49.774 |
| Miami/Hialeah/FL | 273.585 | 137.221 | 103.371 | 95.827 | 94.067 | 82.405 |
| New York/NY | 297.792 | 167.675 | 127.452 | 121.129 | 102.501 | 109.709 |
| Oakland/CA | 132.033 | 70.510 | 73.953 | 64.355 | 50.923 | 38.497 |
| Portland/OR | 115.494 | 90.417 | 69.020 | 51.368 | 43.302 | 26.780 |
| San Francisco/San Mateo/CA | 208.996 | 117.152 | 73.401 | 73.191 | 64.624 | 46.944 |
| San Jose/Santa Cruz/CA | 132.515 | 105.255 | 97.930 | 86.453 | 77.072 | 61.105 |
| Seattle/WA | 140.808 | 112.894 | 82.749 | 74.978 | 58.814 | 39.550 |

*This table displays the coefficient estimates for the linear part of the hotel cost functions.*

## Table A7: Hotel Cost Estimates - Increasing Component

| STR_name | Luxury | Upper Upscale | Upscale | Upper Midscale | Midscale | Economy |
|---|---|---|---|---|---|---|
| Austin/TX | 8.798 | 3.818 | 5.847 | 4.895 | 1.083 | 9.251 |
| Boston/MA | 5.972 | 2.621 | 1.735 | 4.077 | 4.837 | -4.269 |
| Los Angeles/Long Beach/CA | 7.034 | 0.879 | 1.423 | 1.940 | 0.794 | 0.471 |
| Miami/Hialeah/FL | 19.023 | 8.645 | 7.485 | 6.081 | 7.889 | 9.593 |
| New York/NY | 9.179 | 2.694 | 4.034 | 3.835 | 5.226 | 5.124 |
| Oakland/CA | 2.029 | 0.536 | 1.422 | 2.310 | 3.768 | 2.683 |
| Portland/OR | 4.342 | 1.980 | 1.894 | 2.058 | 2.534 | 2.645 |
| San Francisco/San Mateo/CA | 3.998 | 1.745 | 3.658 | 5.805 | 4.603 | 9.900 |
| San Jose/Santa Cruz/CA | 6.425 | 0.403 | 0.590 | 8.548 | 26.883 | 8.561 |
| Seattle/WA | 4.780 | 1.613 | 2.417 | 2.381 | 3.314 | 3.349 |

*This table displays the coefficient estimates for the increasing part of the hotel cost functions. This increasing component operates when occupancy in a hotel option is at least 85% and scales linearly with the quantity of rooms booked.*

## Table A8: Airbnb Mean Costs and Standard Deviation of Costs by City

| | Mean Cost | | | |
|---|---|---|---|---|
| | Airbnb Economy | Airbnb Midscale | Airbnb Upscale | Airbnb Luxury |
| Austin | 90.49 | 122.51 | 161.08 | 225.75 |
| Boston | 73.94 | 104.76 | 131.28 | 181.73 |
| Los Angeles | 81.46 | 113.22 | 138.47 | 190.69 |
| Miami | 100.35 | 134.12 | 170.92 | 239.50 |
| New York | 87.35 | 123.13 | 157.67 | 197.31 |
| Oakland | 69.15 | 94.94 | 111.87 | 148.04 |
| Portland | 64.13 | 80.71 | 98.55 | 129.44 |
| San Francisco | 90.57 | 122.53 | 153.66 | 186.46 |
| San Jose | 75.35 | 101.86 | 121.27 | 156.18 |
| Seattle | 72.09 | 91.91 | 118.21 | 157.99 |
| Standard Deviation | 21.43 | 31.81 | 45.03 | 64.64 |

*This table displays the mean costs for the Airbnb options by city in 2014. The last line displays the estimated standard deviation of costs within each option type.*

Table A9: Competitive Effects on Hotels

| City | Quantity (000's) | | Revenue (MM) | | Profit (MM) | |
|---|---|---|---|---|---|---|
| | Base | Price Adj. | Base | Price Adj. | Base | Price Adj. |
| Austin | 8241 | 8276 | 1043 | 1051 | 180 | 184 |
| Boston | 14025 | 14054 | 2477 | 2484 | 417 | 421 |
| Los Angeles | 28199 | 28417 | 4162 | 4204 | 230 | 241 |
| Miami | 14062 | 14133 | 2642 | 2661 | 375 | 380 |
| New York | 32526 | 32770 | 8830 | 8963 | 1713 | 1783 |
| Oakland | 5452 | 5482 | 635 | 640 | 64 | 66 |
| Portland | 6907 | 6951 | 795 | 802 | 80 | 82 |
| San Francisco | 15714 | 15828 | 3258 | 3299 | 481 | 500 |
| San Jose | 9525 | 9546 | 1410 | 1413 | 126 | 127 |
| Seattle | 11294 | 11317 | 1550 | 1555 | 203 | 205 |
| All | 145946 | 146774 | 26802 | 27071 | 3868 | 3986 |
| All (Compression) | 32552 | 32651 | 7239 | 7309 | 2203 | 2258 |

*This table displays hotel bookings and revenue across counterfactual scenarios. All calculations are for 2014. "Base" refers to the actual data, "Unconstrained Gain" refers to the counterfactual scenario in which the Airbnb option does not exist and hotels can absorb the additional consumers regardless of their actual capacity, and "Price Adjustment Gain" allows hotels to adjust prices in response to no longer having to compete with Airbnb. Row "All" refers to the sum across all cities, and "All (Compression)" refers to the sum across cities for time periods when the city's hotel occupancy was at least 95%.*