Market Structure with the Entry of Peer-to-Peer Platforms: The Case of Hotels and Airbnb

Chiara Farronato,[1] Andrey Fradkin [2]

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Abstract

We study the entry of Airbnb in the accommodations industry to understand the determinants and effects of peer-to-peer growth. We first describe the large heterogeneity of Airbnb's penetration across 50 major US cities (through 2014) and demonstrate that much of this heterogeneity can be explained by proxies for the costs of hotels, the costs of peer hosts, and demand volatility. Second, we show that, on average, a 10% increase in the size of Airbnb reduced hotel revenue by 0.32%. This effect is greatest in cities with relatively low hotel capacity relative to the size of demand. Third, we estimate a structural equilibrium model and use it to study the effects of Airbnb on market outcomes and welfare. On one end of the spectrum, we find that in New York City in 2014 Airbnb increases consumer surplus by 3% and that over 46% of Airbnb bookings would not have resulted in hotel bookings had Airbnb not been available. On the other end of the spectrum, we find that in Las Vegas the aggregate effect of Airbnb is negligible and that 18% of Airbnb bookings constitute market expansion.

[1]Harvard Business School, cfarronato@hbs.edu

[2]MIT Sloan School of Management and Airbnb Inc., afradkin@mit.edu

1 Introduction

The internet has greatly reduced entry and advertising costs across a variety of industries. In particular, peer-to-peer marketplaces such as Airbnb, Uber, and Etsy have enabled small and part-time service providers (peers) to broadly participate in economic exchange. Several of these marketplaces have grown exponentially and have become widely known brands. In this paper, we study the causes and the effects of peer-to-peer entry on the market for short-term accommodations, where Airbnb is the main peer-to-peer platform.

Since its founding in 2008, Airbnb has grown to list more rooms than any hotel group in the world and has intermediated over 60 million trips as of December 2015. However, the number of rooms on Airbnb is highly heterogeneous, both across cities and over time. To understand this heterogeneity, we present a theoretical framework where accommodations can be provided with dedicated or flexible capacity – hotels vs peer hosts. The main difference between dedicated and flexible capacity is that dedicated capacity has higher investment costs while flexible capacity has higher marginal costs.

The diffusion of Airbnb lowers entry and advertising costs of flexible sellers. Given the lower costs, flexible sellers have two decisions to make: whether to enter, and when to produce. We model entry as a longer run decision, which depends on flexible sellers' costs relative to dedicated sellers, and on the trend and variability of demand. Peer entry will thus be larger in cities where hotels have high investment costs, where peers have low costs of hosting, and where the number of travelers is variable over the seasons and growing over time. We confirm that these predictions hold in our data.

In the short-run, flexible sellers decide when to host. Travel is obviously very seasonal: many more people travel on New Year's Eve than in the middle of February. For a flexible seller, it is much more profitable to host in periods of high demand, especially if hotels hit their capacity constraints. Our setting allows us to estimate this short-run elasticity of supply, which we find to be large.

In addition to analyzing entry and production decisions of flexible sellers, our framework allows us to estimate the competitive effects of Airbnb on dedicated sellers. We show that entry of flexible sellers reduces hotel revenues, prices, and occupancy rates, and that this effect is largest in cities where hotel supply is constrained relative to the level of demand.

Finally, we use our model to quantify the benefits of peer entry to consumers. Travelers benefit from the entry of Airbnb because flexible sellers offer a differentiated product relative to hotels, and because they reduce accommodation prices. This is especially true in cities with constrained hotel supply and in periods of high demand. In those cities and periods, flexible sellers allow more travelers to stay in a city without significantly cannibalizing the number of travelers staying at hotels.

We find that for New York, the city with the largest Airbnb supply in our sample, the consumer gains from Airbnb were about 3% of total surplus in 2014. We also find that over 46% of Airbnb bookings would not have been hotel stays had Airbnb not existed. In markets with lower Airbnb penetration, such as Chicago, the consumer surplus and market expansion effects of Airbnb are much smaller. The benefits of Airbnb for both guests and hosts are concentrated in periods of high demand such as New Year's Eve, when many hotels are already operating at full capacity.

Our research relies on proprietary data from Airbnb and data on hotel revenues, prices, and sales for 50 US cities between 2011 and 2014. We use this data to document the heterogeneity in the number of Airbnb listings across cities and over time. Cities like New York and Los Angeles display fast growth in the number of available rooms on Airbnb, while cities like Oklahoma City and Memphis grow much more slowly. Within city, the number of Airbnb rooms is higher in periods like Christmas and summer vacation. 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 in a demand and supply model for accommodations. In this model, hosting services can be provided by dedicated or flexible sellers, and products are differentiated. Dedicated capacity is 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 typically interact with guests before and during the trip. This interaction is time-consuming and sometimes perceived as risky.

The model includes two time-horizons. The long-run horizon is characterized by the entry 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. From a long-run perspective, Airbnb makes it easier for flexible sellers to rent out rooms. The online platform increases the visibility of flexible sellers to travelers, and reduces the risk of hosting strangers with its review system. We model the decision of flexible sellers to join the platform as dependent on the expected returns from hosting, in turn a function of hotels' competition and overall demand.

We define the short-run horizon as one day in one city. In the short-run, 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 demand shocks (e.g. Berry et al. (1995)). On the supply side, hotels compete in a game of differentiated Bertrand competition subject to capacity constraints. Airbnb producers 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 some testable predictions. Long-run entry of flexible sellers will differ across cities. Entry will be largest in cities where hotel investment costs are high, flexible sellers' marginal costs are low, and demand variability is high enough that there are periods when the existing hotel capacity is inefficiently low. In the short-run, flexible sellers will increase competition: they will reduce prices and occupancy of hotels, and the effects will be largest in cities where hotel capacity is low relative to demand.

In Section 3, we confirm that the model predictions hold in the data. We first look at the long-run. We show that peer supply as a share of total supply is larger in cities where it is hard to build 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. 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 to limit the periods with high vacancy rates. 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 focus on the short-run predictions of the effects of flexible supply on hotels. Measurement and endogeneity challenges are discussed in Section 3.X. On average, a 10% increase in the number of available listings on Airbnb reduces hotel revenues by .32%. This effect is due to both a reduction in hotel prices and a reduction in room 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 revenues by .64%. 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.

In Section 4, we describe our estimation strategy of the model from Section 2. We estimate the cost of joining Airbnb from the entry decision of flexible sellers, and use variation in time and city characteristics. We estimate travelers' utility from each accommodation option and hotels' marginal costs in a framework similar to BLP. Finally we estimate the marginal cost distribution of hosts on Airbnb assuming that they take prices as given. Together, these estimates allow us to measure consumer and producer surplus, as well as counterfactual scenarios without Airbnb.

Section 5 presents our results. We find that consumers' utility for Airbnb is lower than for hotels, but that preferences for Airbnb increase between 2011 and 2014. By the end of the sample period the mean utility from an entire Airbnb property exceeds the mean utility of economy 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, but that the cost distribution of peer costs makes flexible supply highly elastic.

In the absence of Airbnb, total welfare would be lower, but hotels would gain at the expense of flexible sellers and consumers. We find that for New York, the city with the largest Airbnb supply in our sample, consumer surplus would be 3% lower if Airbnb did not exist in 2014. This is because fewer travelers would book rooms, and travelers who end up booking hotel rooms would pay higher prices. In particular, we find that over 46% of Airbnb bookings in New York would not have been hotel stays had Airbnb not existed. Other cities like San Francisco and Los Angeles experience consumer surplus gains between 1 and 1.6%.

We also find that the gains from Airbnb are especially large during high demand periods in cities where the hotel sector is operating at peak capacity. For example, on high-demand days in New York, consumer surplus is 5.3% larger than without Airbnb. In cities with lower Airbnb penetration, the effects of Airbnb are much smaller. For example, the consumer surplus gain is 0.4% in Chicago and as low as .04% in Las Vegas.

We also find that if we hold hotel prices fixed, Airbnb's effects on hotel bookings have been relatively small. For example, we find that had Airbnb not been operating in New York, hotel room nights booked would have increased by 2.5% in 2014 (2.3% in SF and 1.6% in LA). The effects of Airbnb on hotel occupancy are even smaller in other cities, such as Las Vegas (0.08%) or Chicago (0.53%).

In NY, LA, and SF, the large effects on consumer surplus and small effects on hotel bookings are the result of two related factors. First, because the hotel sector has limited capacity, additional bookings on Airbnb cannot be allocated to additional bookings at hotels during periods of peak demand. Second, the supply of Airbnb rooms varies positively with market demand and many hosts are on the margin of hosting. When demand rises, these peer hosts find it advantageous to host and therefore increase Airbnb supply exactly when demand is highest.

Our paper contributes 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 (e.g. Zervas et al. (2015) on Airbnb, Seamans and Zhu (2014) and Kroft and Pope (2014) on Craigslist, and Aguiar and Waldfogel (2015) on Spotify). We extend the analysis to include the more general effects on consumers and service providers on the new platform. With our estimates of short-run supply elasticity, we confirm the results of Cullen and Farronato (2014), Hall et al. (2016), and Chen and Sheldon (2015), who find that labor supply is very elastic on TaskRabbit and Uber. 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)).

The paper is structured as follows. In the next section, we present the data and the 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 elasticity of flexible supply, and on the spillover effects of Airbnb on hotels. Section 4 presents our empirical strategy for estimating the theoretical 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 to strangers of an apartment or room. 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 trust. While Airbnb is not the only company serving this market, it is the dominant platform in most US cities.[1] 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 fast in the aggregate, but the growth has been highly 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.[2] Even among the top 10 cities, there are fast growing markets like San Francisco and New York, as well as slow growing markets like Chicago and DC. This growth is specific to the

[1] The most prominent competitor is Homeaway/VRBO, a public company whose business has historically been concentrated in rentals of entire homes in traditional vacation markets such as beach and skiing destinations.

[2] 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 normalize the number of Airbnb listings by the number of total housing units within an MSA.

peer-to-peer sector and does not represent a broader growth of the supply of short-term accommodations (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 more prominently displayed in New York in Figure 1, which experiences large spikes in available rooms during New Year's Eve and the summer season, and in Austin during the South by Southwest festival. From the picture it seems that a lot more people are willing to host in periods of high demand like New Year's Eve or South by Southwest than in periods of low demand.

Figure 1 suggests that the decision of hosts to be available on Airbnb differs both across cities and over time. In certain cities, and during specific periods the returns to hosting are especially high, and Airbnb hosts flexibly choose when to rent their spare rooms. This stylized fact motivates our theoretical model, in which we distinguish between dedicated and flexible sellers, or hotels and 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.

We consider a market where hosting services can be provided by professional and flexible sellers and products are differentiated. The model has a short-run component, which determines daily prices and rooms sold for hotels and Airbnb as a function of installed dedicated and flexible capacity, and the demand state. It also has a long-run component where flexible sellers decide to enter as a function of pre-determined hotel capacity, and the distribution of demand states.

We start by presenting the short-run model of daily demand and supply of rooms. 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 distribution F, where F can be interpreted as the distribution of demand states over the course of a year. Hotels and Airbnb rooms are differentiated products. $Q_i^d(p_i, p_j)$ is the residual demand for product i (hotel or Airbnb room) 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, hotels set prices and at the same time Airbnb sellers choose whether to host. We assume that hotels face marginal cost c_h to book one room for one night, and they can coordinate to maximize joint profits subject to their capacity constraint:[3]

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

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:

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

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

The market equilibrium consists of prices and quantities for hotels 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. Hotel profits per available room, as well as both prices and occupancy rates, are lower if K_a is higher. In addition, for the same level of K_a, hotel profits will be reduced relatively more if their capacity constraint is often binding. This is because if demand is high relative to hotel capacity, the price equilibrium will be higher, and this will push more flexible suppliers to produce and cannibalize dedicated suppliers. 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. Intuitively, this occurs because the increase in flexible capacity affects hotels through a reduction in their residual demand, and when hotels are capacity constrained, their supply curve is vertical. A marginal downward shift in residual demand will have no effect on quantity and a large effect on price if supply is perfectly inelastic. Appendix A provides formal proofs, and Section 3.2 tests these predictions.

In the long-run, entry decisions are made. We do not model hotel entry, and instead assume that K_h was optimally set knowing $F(d)$ but in the absence of Airbnb or flexible sellers ($K_a = 0$). 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 of joining the platform C, randomly drawn from a given distribution, and that their time horizon coincides with the distribution

[3] More details on the assumption that hotels have market power can be found in Section 4.

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. Obviously a higher level of demand in every state is more attractive, but, perhaps less so 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. The appendix contains formal proof of these predictions, which hold in the data (Section **??**).

Note that in the long-run, if hotels were allowed to re-optimize their capacity, peer entry could also crowd out some dedicated sellers, something we cannot consider in the current paper given the short time-horizon of our data. Exploring exit of dedicated producers would be a valuable extension to our current work. In the next section, we show how our empirical context fits nicely within the predictions of our theoretical model.

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 (private rooms or entire apartments).[4] 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 be 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 (according to the calendar) or is available for at least one date in the future.

[4]Shared rooms, a third type of listing offered on Airbnb, are very rare.

The hotel data come from Smith Travel Research (STR), an accommodations 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.[5] STR obtains its information by running a periodic survey of hotels. For the 50 largest markets, an average of 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 seven 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 slightly higher prices (\$110) and much lower occupancy rates (12%). 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 \$9 (\$25 for Airbnb prices), while the city at the 75th percentile has a standard deviation of \$21 (\$35 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 share of available rooms as of December 2014 is 3%, and in most cities it is between 1% and 4% (25th and 75th percentiles). Two other normalizations confirm that Airbnb was still small in most US cities as of December 2014. Across all cities, Airbnb bookings represent 4% of all potential guests, and represent less than 1% of total housing units for all MSAs in our sample.

3.1 The Long-Run: Drivers of Peer Entry

In this section, we verify the theoretical predictions regarding the long-run growth of the peer-to-peer sector from Section 2.1. Even if 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 between 2011 and 2014, our sample period. So to look at the long-run entry decision of peer producers, we take a snapshot as of December 2014, the end of our period. With some assumptions on the diffusion process of Airbnb and given the growth rates in Figure 1, we discuss the equilibrium size of peer supply across our cities in Section 5.

[5] 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`

Figure 2 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 peer-to-peer penetration.

In Section 2.1 we demonstrated how the profitability of hosting for flexible sellers in a given city depends on relative costs. If professional sellers' investment costs are high or flexible sellers tend to have low marginal costs, profitability for peer producers will be high, and consequently we will observe more entry of peers. We use two proxies for hotel costs of capacity. 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).[6] Figure 3 (and A2 in the Appendix) confirms that constraints to hotel capacity are good predictors of Airbnb penetration in a city.[7]

Another cost factor influencing the viability of peer production is the marginal cost of peers. 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 4 plots the share of flexible supply at the end of 2014 against the percentage of unmarried adults (in Appendix Figure A3 we plot the share of Airbnb against the percentage of children in the population). Both figures verify that cities where more unmarried adults and less children live are those where Airbnb has indeed spread more.

In addition to cost factors, travelers' demand affects peer entry, in particular its variability and growth. This is due to two related reasons. First, when demand is variable, the efficient form of production includes some capacity that operates only part of the time. Dedicated capacity is less efficient if used only some of the time. In contrast, flexible sellers are able to provide supply only in times when that supply is especially valuable. Second, if dedicated sellers must pre-commit to capacity, unforeseen growth in demand will create an inefficiently

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

[7] 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 A4 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.

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.[8] First, since the construction of new hotels takes a long time while hosting on Airbnb can happen overnight, unexpected growth in demand will result in greater peer entry. Figure 5 confirms this intuition by showing that the 2012-2011 growth rate in travelers for each city is positively related to Airbnb penetration in 2014. Figure 6 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 large.

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 as of December 2014 and the explanatory variables are combinations of the measures of relative costs, demand growth, and demand variability described above. Despite the small sample size, all factors affect the size of Airbnb in the expected direction, and three out of four - hotel investment costs, peers' marginal costs, and demand volatility - are statistically significant. In addition, the R-squared confirms that more than 50% of the variation in the size of Airbnb is explained by these cost and demand characteristics.

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 Airbnb 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.

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

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 7 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 number of unadjusted available listings (blue line) actually decreases during New Year's Eve. One reason for this is that calendar updating behavior is endogenous. Many hosts do not pro-actively take the effort to block a date on their calendar when they are unavailable. However, when they receive a request to book a room, they typically reject the guest and update their calendar accordingly. Since a larger share of listings receive 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). The third relevant fact from Figure 7 is that 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.

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. And even if it overstates the "true" number of available rooms in the market, it's a consistent measure of the size of Airbnb over time. Figure 7 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 7 it is clear that Airbnb bookings fluctuate over time: more rooms are booked during high traveling seasons than in other periods. Here, we provide preliminary evidence suggesting that flexible supply is highly elastic, and almost twice as elastic as dedicated supply. The high elasticity of flexible supply is not a result of our model, but rather an assumption implicit in the distinction between flexible and dedicated capacity. Here we confirm this assumption with preliminary OLS regressions. In the structural model in Section 4 we will back out the underlying cost structure of peers and hotels that give rise to these elasticities.

We estimate the average elasticity of hotel and Airbnb bookings with respect to their prices with 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. κ is the elasticity of supply with respect to prices, and will be different between flexible and dedicated supply. μ_{mt} includes city, seasonality (quarter-year), and day of week fixed effects to control for the fact that costs might change by city or over time (e.g., on Airbnb hosts are more likely to list their room as available in some cities or when they go on vacation).

The equation still suffers from simultaneity bias because the price of accommodation is correlated with unobserved fluctuations in hosting costs. 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.[9]

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 returing) flight travelers in a city-month, which we used in Section 3.1. The second comes from Google Trends, which provide 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 detrend 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 contemporaneous search volume as instrument, although adding lags 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 on hotel revenues.

Table 4 contains our estimates of Equation 3 for Airbnb and hotels separately. Turning

[9]We do not worry about the same endogeneity issue for hotels because we assume hotel capacity is 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.

first to column (1), a 1% increase in the average hotel daily rate increases hotel bookings by 1.4%. This elasticity is just over half as large as that of Airbnb (column 2), whose estimated elasticity is 2.5. Our estimates of χ, the elasticity of bookings with respect to available listings, is equal to 1 for hotels, and 0.56 for Airbnb. This implies that while doubling available hotel rooms doubles bookings, the effect of doubling Airbnb rooms is just over half as large. This is because a significant portion of seemingly available listings are not actually available at the price levels observed in the data, and is partly a result of the lack of calendar updating discussed at the beginning of this section.

The table shows 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. Next, we study the effect that flexbile supply has on hotels.

Peers' Effects 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. First, 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, that 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 current idiosyncratic demand shocks. [10]

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

[10]In Appendix C we conduct robustness checks to demonstrate that these controls and the instruments likely capture all the potential sources of endogeneity.

the measure of Google searches for hotels in the city, $travelers_{mt}$ is the number of arriving air passengers, and θ_{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 α, which is the average short-run elasticity of hotel outcomes to peers' supply over our sample period. The coefficient is identified from variation across cities and over time in the number of available listings due to increasing awareness of Airbnb, and from variation in the availability of hosts due to their travel plans outside of the city, which we assume are uncorrelated with daily demand for accommodation within the city.

Table 5 displays the results of the baseline specification. The estimated elasticity for hotel revenue is -.038, implying that a 10% increase in available listings decreases the revenue per hotel room by 0.32%. 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 occupancy rates but not on prices. Appendix C discusses the robustness of our finding to other measures of Airbnb supply and instrumentation strategies, and Tables A1 and A2 separate the effect by hotel scale and Airbnb room type.

Our theoretical model from Section 2.1 predicts that the effects should be largest in cities with binding hotel capacity constraints. To test this, we split the sample in 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.

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. The coefficient on Airbnb in this specification is -.08 for the supply-constrained cities and a statistically insignificant -.04 for the non-constrained cities. The effect is mostly due to a price reduction in the constrained cities (column 3) while it is due to a decrease in occupancy in the non-constrained cities (column 5).

This difference in effects occurs for two reasons. First, for the same level of Airbnb and hotel capacity, the effect of Airbnb is larger 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 Airbnb is big. 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, the average maximum Airbnb supply share in supply-constrained cities is 4.6% while it's only in 1.7% in unconstrained cities, and the average hotel occupancy rate is 69% in constrained cities, and only 63% in unconstrained cities.

The remaining columns of Table 6 show the effects of Airbnb on occupancy and price. For supply constrained cities, there are effects on both price and occupancy, with a larger effect on price. On the other hand, there is no statistically significant effect of Airbnb on price for supply unconstrained cities. This is consistent with the fact that binding capacity constraints lead to spikes in hotel prices. 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 in constrained markets have more room to adjust on the price margin than hotels in non-constrained markets.

To summarize Section 3, we have carried out a series of tests of our theoretical model from Section 2. We have shown that 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 25%, against 14% for hotels. Finally, we have shown that the entry of flexible supply has negative spillovers on the revenue of dedicated suppliers, and that this effect is higher in cities with binding hotel capacity constraints. In the rest of the paper, we structurally estimate our 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 econometric version of our model that we take to the data. We start with the description of equilibrium for a given market n, defined by day t in city m. Our model is related to the standard differentiated demand model of Berry et al. (1995) with three key differences. First, we assume we know the marginal costs of hosting when computing firm's equilibrium pricing decisions. Second, because hotels are capacity constrained, we only use supply side moments from observations in which realized demand for a particular hotel type is below its capacity. Third, we model the supply of peers in the market as perfectly competitive and estimate their supply function separately.

Consumer Demand

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

$$u_{ijn} = \mu_{jn} - \alpha_i p_{jn} + \epsilon_{ijn} \tag{5}$$

where μ_{jn} are market-specific mean utilities for each accommodation (different hotel scales and Airbnb listing types), p_{jn} is the price of a good, and ϵ_{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:

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

where D_n is the market size, and H is the distribution of the random coefficient on price α, assumed to be normal with mean $\bar{\alpha}$.

A key choice in our model is D_n, i.e. the total number of consumers potentially booking in the market during a given time period. While we plan to conduct extensive robustness checks, we initially set the potential number of trips equal to twice the maximum number of rooms booked in the sample for each market. The model is flexible enough to allow for both a market expansion and cannibalization effect as long as the number of consumers exceeds the maximum number of rooms booked. To see this, consider two dates with the same observables and where one observation has many Airbnb bookings while the other does not because Airbnb was small. The model would find a large market expansion effect if the number of hotel bookings did not change whereas it would find a large market cannibalization effect if the number of hotel bookings decreased by the same amount as the increase in Airbnb bookings.

Hotel Supply

Hotels of type h, where $h \in \{$*luxury, upper-upscale, upscale, upper-midscale, midscale, economy, independent*$\}$, have room capacity K_{hn} and marginal cost c_{hn}, which we assume to be constant for each city-hotel type combination. We view this assumption as reasonable for two reasons. First, the main cost of hosting someone is the labor cost of cleaning in a city, which rarely changes in the short-run. Second, according to Kalnins (2006), hotels typically price significantly above marginal cost to preserve brand reputation. This incentive to preserve the brand is unlikely to vary in the short-run. In our model, each hotel type competes with other hotel types and peer supply. We assume that this competition takes the form of

Bertrand-Nash equilibrium with capacity constraints. Therefore in every market each hotel type solves the following profit maximization problem:

$$\begin{aligned} &\underset{p_h}{Max}(p_h - c_{hm})Q(p_h, p_{-hn}, p_{an}) \\ &s.t.\ Q(p_h, p_{-hn}, p_{an}) \leq K_{hn}, \end{aligned} \tag{7}$$

where p_{-hn} includes the prices of other hotel types, and p_{an} includes the prices of Airbnb room types. c_{hm} is a city and scale-specific marginal cost. This is analogous to Equation 1 allowing for different types of hotels and different types of Airbnb. Note that the standard first order pricing condition holds only in cases where the capacity constraint does not bind. In other cases, the price is set to equate residual demand to hotel capacity. Therefore, in the estimation we will only use supply-side moments from days when a specific hotel scale is not booked out.

Peer Supply

Peers of each type a (reviewed/non-reviewed private rooms/entire properties) with total available listings K_{an}, take prices as given. Hosts draw marginal costs from a normal distribution with parameters μ_{an} and σ_{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:

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

As in the case of hotels, this equation is the extension of Equation 2 when there are multiple room types within hotels and Airbnb listings.

Equilibrium

The market equilibrium consists of prices and quantities for hotels and peers $(p_{hn}, p_{an}, Q_{hn}, Q_{an})$ such that consumers maximize utility, hotels and peers maximize profits, and their optimal choices are consistent with one another.

4.1 Estimation Strategy

We estimate the model described above using the generalized method of moments. The important choices in this model are the moments to match and the instruments used. We estimate demand and hotel supply jointly, while Airbnb supply is estimated separately.

The reason that we jointly estimate supply and demand is that much of the variation in the data is due to demand shifts due to seasonality. Using the hotels' optimality conditions gives us additional power in identifying the elasticity of demand, which is a key parameter needed to measure consumer welfare and how it is affected by the entry of Airbnb.

The supply of Airbnb rooms can instead be estimated separately given our assumption that peer hosts take prices as given.

The demand side is a standard BLP specifiction (Berry et al. (1995)) with one random coefficient on price. Our set of demand-side moments include:

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

We parametrize $\hat{\hat{\delta}}_{jn} = -\bar{\alpha}p_{jn} + \mu_{jm} + \beta X_n$, where the components are observable shifters of the demand for relative types of accommodation. These include accommodation type fixed effects, as well as airbnb and hotel-specific time trends which control for the fact that Airbnb might become more attractive relative to hotels over time. X_n also include market specific drivers of demand proxied by month fixed effects to control for seasonality, and de-trended Google searches.

Z_{1jn} include all the variables in μ_{jn} and X_n, as well as supply-side shifters that affect prices without affecting total demand or preferences across accommodation types. The supply side shifters of prices include the 30-day lag of available Airbnb listings interacted with the accommodation types. The idea is that a larger aggregate size of Airbnb in a city will affect each hotel and Airbnb listing type's current prices.

On the hotel supply side, we use the following pricing moments:

$$m_{2jn} = \left[\mathbb{1}_{q_{hn}<\bar{Q}_{hn}}(p_{jn} - \hat{p}_{jn})\right] Z_{2jn} \tag{10}$$

where the predicted price depends on the first order condition in 7. We only use days for which hotels are not constrained by their maximum capacity in this set of moments because prices on days when hotels are constrained by their total number of rooms do not reflect the first order condition.[11] We define that a hotel scale is constrained in a given market if occupancy rate is 92.5% or higher. Z_{2jn} include city-specific hotel type dummies and the Google trends series for hotel searches in the city. Note that we cannot interpret pricing errors as unobserved costs because marginal costs are unlikely to change from week to week in the hotel sector. Instead, to the extent that the model-predicted prices do not match the actual prices, we rationalize this as an optimization error.

[11]Prices on constrained dates can be used to derive inequality constraints on the costs but we obtain precise estimates even without these additional restrictions.

Lastly, the supply Airbnb can be estimated separately using a linear instrumental variables regression. Equation 8 implies that $\Phi^{-1}\left(\frac{Q_{an}}{K_{an}}\right) = \frac{\mu_{am}}{\sigma_{am}} + \frac{1}{\sigma_{am}} p_{an}$, 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

$$\Phi^{-1}\left(\frac{Q_{an}}{K_{an}}\right) = \beta_a p_{an} + \gamma_a X_{an} + \epsilon_{an}, \tag{11}$$

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. After estimating the above equation, we can transform the coefficients into the peers' cost parameters.

$$\sigma_a = \frac{1}{\beta_a},\ \mu_{an} = \frac{\gamma_a \bar{X}_a + \epsilon_{an}}{\beta_a} \tag{12}$$

These cost parameters allow us to estimate the surplus of peers from hosting and to model endogenous responses of hosts to changes in market conditions.

5 Results

In this section we discuss the results of our estimation. We first study the variation in substitutability between hotels and Airbnb across the major cities. Then we consider consumer surplus and hotel occupancy in counterfactuals without Airbnb. We show that the gains in consumer surplus are much larger in cities where hotel capacity is small relative to demand peaks. Furthemore, most of the surplus increase originates from market expansion during periods of high demand. Finally, we estimate peer hosts' surplus.

5.1 Demand Estimates

We estimate the random coefficients model separately for five major US cities. Table 8 displays coefficient estimates for each city separately. Turning first to the distribution of price coefficients, we estimate a positive and statistically significant mean for each city. Second, the standard deviation of the price coefficient is 50% less than the average for each city. These estimates imply relatively price elastic consumers, as tables 10 and 11 show.

Next we turn to the mean utilities of the hotel types. We find that, as expected, the mean utility from a hotel type decreases in the quality of the hotel, with luxury hotels having the highest value and economy the lowest. We find that independent hotels are approximately comparable to the quality of an upper-upscale hotel.

The Airbnb-specific estimates are also in line with expectations. We find that entire properties yield more utility than private rooms and reviewed properties yield more utility than non-reviewed properties. At the beginning of our sample in 2011, reviewed entire properties on Airbnb are, on average, valued less than even economy hotel rooms. However, because we find a positive and statistically significant Airbnb specific trend in all markets, this perception changes by 2014. Due to this trend, the mean utility from a reviewed entire property exceeds the value of economy and midscale hotels in Los Angeles, New York, and San Francisco by the end of 2014. Lastly, we find that our demand proxy, Google Trends, has a positive and statistically significant effect on the utility of accommodations and that all of the cities experienced a positive trend in consumers' utility for accommodations.

Table 9 displays the coefficients from Table 8 but divided by the estimated mean α so that the coefficients can be interpreted in dollars. The time trends are also taken into account, so that our comparisons across accommodation options relate to the end of our period. Our estimates imply reasonable differences in nightly values across hotel types. For example, a luxury hotel in Chicago is worth \$101 more per night on average than an economy hotel. In New York, this difference rises to \$260, and is commensurate with the difference in observed prices between these options. In levels, the mean utility from any accommodation option in New York, San Francisco, and Los Angeles is higher than in Las Vegas and Chicago.

The table also allows us to discuss the relative preferences of consumers for of hotel and Airbnb rooms. In particular, if we look at the dollar difference in mean utility between economy or midscale hotels and the best Airbnb option (reviewed entire properties), we see that this difference is between \$45 and \$60 in Chicago and Las Vegas, while it is even negative in SF, NY, and LA. This implies that while in Chicago and Las Vegas economy and midscale hotels are valued about \$50 more than the best Airbnb option, in New York, San Francisco, and Los Angeles they are actually valued about \$20 less than reviewed entire apartments on Airbnb. As we will see in the next section, this city heterogeneity has important implications for the overall effect of Airbnb in those cities, smaller in Chicago and Las Vegas, and larger for the other three cities.

5.2 Consumer Surplus and Market Expansion

In this section we discuss the implications of our demand estimates for consumer surplus and the competitive effects of peer hosts on hotels. For consumer surplus, we first look at its increase due to the fact that Airbnb offers a new option which is a substitute to both hotels and the outside option. We then incorporate the hotel capacity constraints and evaluate by how much Airbnb can alleviate these constraints in the accommodation market. Lastly, we consider the scenario where hotels can adjust prices upward in the absence of Airbnb.

Table 12 displays consumer surplus generated by the accommodations industry in our baseline scenario with the presence of Airbnb. Accommodations in New York generate $413 million and accommodations in San Francisco generate $120 million for Saturday nights in 2014. Across all cities, the value generated by the industry is increasing over time.

We first compute expected consumers' utilities and booking probabilities in the absence of Airbnb, but we keep hotels' prices constant at the observed levels and we allow hotels to absorb any additional Airbnb guests without worrying about capacity constraints. In this scenario, we find that the effects of Airbnb vary across cities and over time. First, the positive effect of Airbnb on consumer surplus and total bookings increase over time. This is due both to the increase in consumers' value of Airbnb over time and to the growth of listings that are available on the site. Second, the benefit from Airbnb is greatest in New York and lowest in Las Vegas: in the absence of Airbnb, consumer surplus would have been 2.82% lower in New York and only 0.04% lower in Las Vegas in 2014.

For our second counterfactual, we impose that hotels have limited capacity. This means that hotels can accommodate the maximum between the observed number of rooms sold on a given night and 92.5% of their available rooms. In such a scenario, without price adjustment, some guests will necessarily be constrained out of the market. We compute consumer surplus and booking probabilities using the following algorithm. We first compute the most constrained hotel option as the one which would hit its constraint with the fewest number of potential consumers. We then randomly divide consumers into those that have the choice between all options and those that are rationed out of the constrained hotel option. The non-constrained consumers make their picks and we repeat the algorithm with the remaining consumers and the second most constrained option. This process continues until all consumers have chosen.

Columns 3 and 7 of Table 12 display the effects of Airbnb if we impose the constraints. In this scenario, the benefits of Airbnb increase even more because peer hosts help accommodate peak demand. For example, the consumer surplus in New York increases from 2.82% to 4.34% and the increase in room-nights booked changes from 2% to 3.4%. Of course this is true for New York, but not for Las Vegas, a city where hotels rarely hit their capacity constraints. Lastly, Columns 4 and 8 focus on a subset of high-demand Saturday nights in our sample, those when at least one hotel scale hits 92.5% occupancy rate. The benefit of Airbnb is especially large on those nights, when the absence of Airbnb leads to a 5.25% decrease in consumer surplus in New York, or a 3.95% decrease in San Francisco. On the other hand, the overall effect of Airbnb remains much smaller in non-constrained markets like Las Vegas and Chicago, when the change in surplus is respectively 0.06% and 0.84%.

In our third counterfactual, we allow hotels to adjust prices. To do so, we solve for new equilibrium quantities and prices in a scenario without Airbnb. We use the model implied cost and demand shocks for this procedure. One complication is that we do not observe the cost of hotels when they are constrained. Therefore, we impute their cost but taking the average of the observed costs in the prior 8 weeks. If no costs are available in the prior 8 weeks, we assume that the time specific cost shock is 0. We plan to improve on this procedure in future versions of the paper.

Our estimates help us assess the effect of Airbnb on hotels. Table 13 shows the percentage increase in total bookings for hotels in the counterfactual scenarios without Airbnb. If capacity constraints are not imposed, hotels gain between .08% of bookings in Las Vegas and 2.49% in New York in the absence of Airbnb in 2014. However, since sales increase especially in periods of high demand, and hotels are often already operating at full capacity, this occupancy increase is a large overestimate. Indeed, this percentage gain decreases once capacity constraints are imposed. For example, the percent of room nights gained in a scenario without Airbnb drops from 2.49 to 1.06 once we account for hotel constraints in New York in 2014. Lastly, if we also allow hotels to adjust prices, this number falls further to .93. If we only consider high-demand days, the hotel loss in bookings due to Airbnb is less than 1% in New York. Alternatively, the change in hotels' occupancy in Las Vegas is always around 0.07% regardless of capacity constraints, due to the fact that hotels there are rarely at full capacity.

Lastly, we turn to the question of market expansion versus cannibalization. If Airbnb is simply a hotel substitute then the addition of Airbnb would take away from bookings in hotels, as long as hotels have excess capacity. However, if Airbnb represents a differentiated product which some people intrinsically prefer to hotels, then Airbnb bookings may have expanded the market. In Table 14 we display the number of observed Airbnb room nights and the share of them which would not have translated into hotel bookings in our model. We find that the market expansion effect is large and varies greatly across cities. In New York, 46% of Airbnb travelers would not have booked a hotel in the scenario without hotel capacity constraints. With constraints, this number rises to 70% for 2014. Alternatively, in Las Vegas, the market expansion effect is just 18% without constraints and 28% with constraints in 2014.

In summary, consumers' benefits from the entry of Airbnb are heterogeneous across cities and over time. In cities with a constrained hotel sector, consumers benefit the most since the expansion of capacity allows more travelers to book an available room. This is especially true in periods of high demand, like New Year's Eve. Since most of the benefits to consumers originate in constrained cities and high demand periods, the reduction in occupancy of hotels due to Airbnb is very limited: hotels would have operated at full capacity in any case.

5.3 Peer Costs and Surplus

Peer hosts represent the last of the three agent types affected by the spread of peer-to-peer marketplaces. Below we discuss the results regarding the estimated cost distributions of peers and the implications of those cost distributions for peer surplus.

Recall that we assumed the cost distribution was normal with an unknown mean and standard deviation. Table 15 displays the estimated mean and standard deviation of the cost distribution for Airbnb hosts in New York, and figure 8 shows the fluctuations in mean costs over time. For all room types, the mean costs exceed the mean prices that listings transact at. This occurs because fewer than 50% of active listings typically transact. Across all room types, there is economically and statistically significant dispersion in the cost distribution. Lastly, the mean costs of non-reviewed listings exceed those of reviewed listings for private rooms. Differences between the costs of reviewed and non-reviewed listings may be driven by selection and quality. Listings with low costs transact quickly and become reviewed, thus leaving only high cost non-reviewed listings active on the site. Alternatively, and this seems to be true for entire apartments, since non-reviewed listings are less valued by guests on average, then even with lower costs these listings may transact less frequently.

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.

$$PS_{an} = \int_{-Inf}^{p_{an}} (p_{an} - max(c, 0)) dF_{an}(c) \tag{13}$$

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 16 displays average surplus per booking, total surplus, and average price for five markets (Chicago, Las Vegas, Los Angeles, New York, and San Francisco) between 2011 and December 2014. Note, because our estimates use only Saturday nights, the total surplus figures don't represent the overall surplus from Airbnb. In 2014, the typical surplus per night ranges between \$24 in Las Vegas and \$33 in San Francisco. This surplus represents a 18% mark-up over costs in New York in 2014, suggesting that Airbnb provides value well in excess of the opportunity cost of hosting. The results also suggest that the surplus per night has increased over time.

Total surplus (columns 4 through 6) increased by a larger percentage than average surplus over this period due to the increase in overall bookings. Not surprisingly, the largest peer surplus across the five cities occurs in New York because, the city with the most listings and the most bookings. For 2014, the Saturday night peer surplus was $6.6 million, more than 50% higher than in 2013. There is also a large difference in Airbnb activity on days which are hotel constrained and days which are not. Table 17 breaks out the average peer surplus per night across cities and room types by whether the occupancy rate for at least one hotel type was over 92.5%. The peer surplus on constrained days is much larger than on unconstrained days across all cities and room types. This result demonstrates once again the importance of supply constraints in this market and the value of a peer-to-peer platform in alleviating these constraints.

6 Conclusion

In this paper we have studied the economics of peer production in the industry for shot-term accommodation. The focus of this paper was to quantify the effects of the spread of this new form of production on consumers, peers, and incumbent firms (hotels). We began the paper by showing 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. This motivated our reduced form specification 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 .32%. We then showed that the effect varies across cities and listing types. We found larger effects of Airbnb in cities with constrained hotel sectors and in markets with relatively more private rooms rather than entire properties listed.

Next, we developed a structural model of equilibrium in this industry to study the surplus and market expansion effects of Airbnb. We found that in New York, the markets where it has been most successful, Airbnb increased consumer surplus by 3% and that most Airbnb bookings originated from market expansion rather than business stealing. In other cities with smaller Airbnb presence, such as Las Vegas, the effects on surplus and market expansion were smaller. Lastly, we showed that the benefits to consumers and peers of this platform are concentrated on high demand days when hotels are already operating at peak capacity.

Our data only extend through the end of 2014. Since then, Airbnb has continued its rapid growth in both number of listings and global awareness. While we cannot say for sure what 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 nonetheless valued by consumers. Second, the hotel sector in many cities is frequently constrained and cannot host many travelers during peaks in demand. It is exactly in this time periods that peer production ramps up and absorbs this excess demand, increasing the total size of the market and consumer surplus.

We've 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 important spillovers into other markets including the labor market and the housing market. We leave the study of these effects for future work.

References

Aguiar, Luis, and Joel Waldfogel. 2015. "Streaming Reaches Flood Stage: Does Spotify Stimulate or Depress Music Sales?" National Bureau of Economic Research Working Paper 21653.

Bass, Frank. 1969. "A New Product Growth for Model Consumer Durables." *Management Science*, 15(5): 215–227.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica*, 63(4): 841–890.

Bulow, Jeremy I., John D. Geanakoplos, and Paul D. Klemperer. 1985. "Multimarket Oligopoly: Strategic Substitutes and Complements." *Journal of Political Economy*, 93(3): 488–511.

Chen, K. M., and Michael Sheldon. 2015. "Dynamic pricing in a labor market: Surge pricing and flexible work on the Uber platform." Mimeo, UCLA.

Cullen, Zoë, and Chiara Farronato. 2014. "Outsourcing tasks online: Matching supply and demand on peer-to-peer internet platforms."

Gyourko, J., A. Saiz, and A. Summers. 2008. "A new measure of the local regulatory environment for housing markets: The Wharton Residential Land Use Regulatory Index." *Urban Studies*, 45(3): 693–729.

Hall, Jonathan, Cory Kendrick, and Chris Nosko. 2016. "The Effects of Uber's Surge Pricing: A Case Study."

Kalnins, Arturs. 2006. "Markets: The U.S. Lodging Industry." *The Journal of Economic Perspectives*, 20(4).

Kroft, Kory, and Devin G. Pope. 2014. "Does Online Search Crowd Out Traditional Search and Improve Matching Efficiency? Evidence from Craigslist." *Journal of Labor Economics*, 32(2): 259–303.

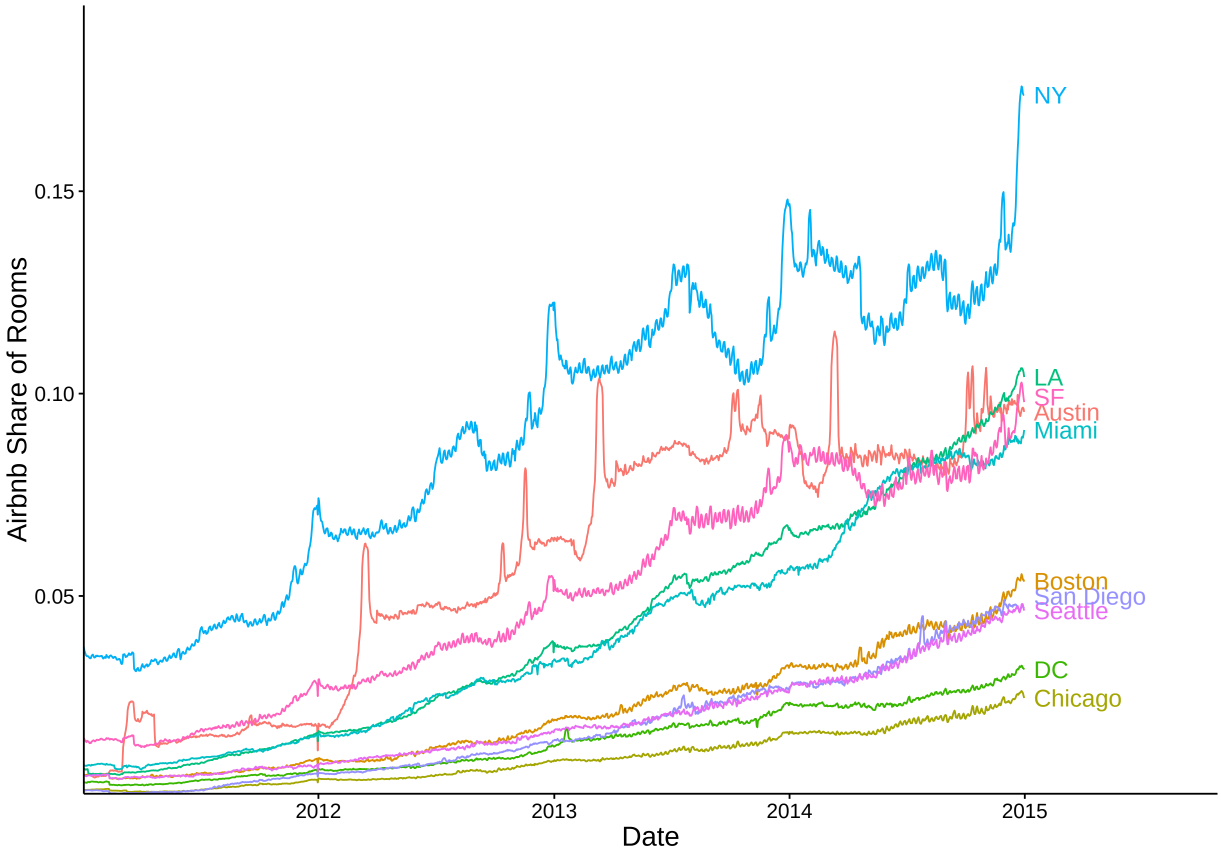
Saiz, Albert. 2010. "The Geographic Determinants of Housing Supply." *The Quarterly Journal of Economics*, 125(3): 1253–1296.

Seamans, Robert, and Feng Zhu. 2014. "Responses to Entry in Multi-Sided Markets: The Impact of Craigslist on Local Newspapers." *Management Science*, 60(2): 476–493.

Zervas, Georgios, Davide Proserpio, and John Byers. 2015. "The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry." Social Science Research Network SSRN Scholarly Paper ID 2366898, Rochester, NY.

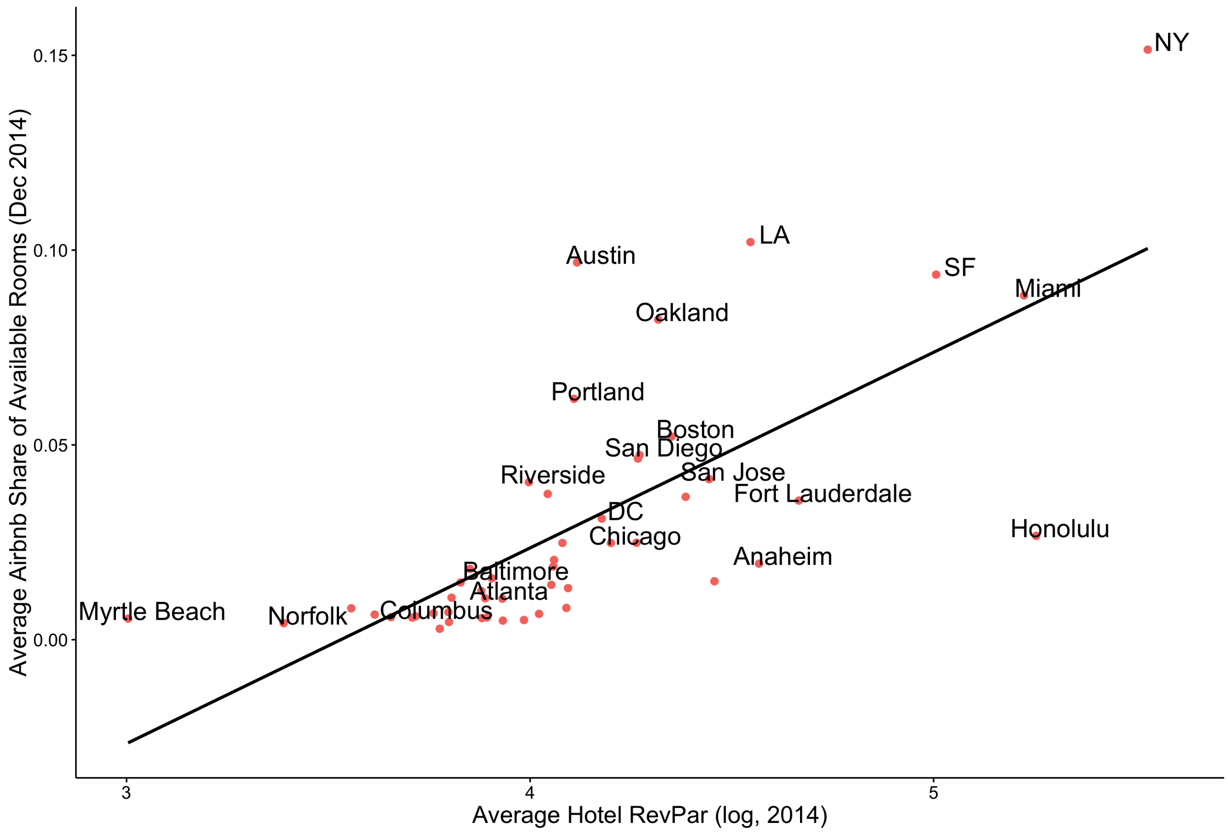
Tables and Figures

Figure 1: Growth of Airbnb



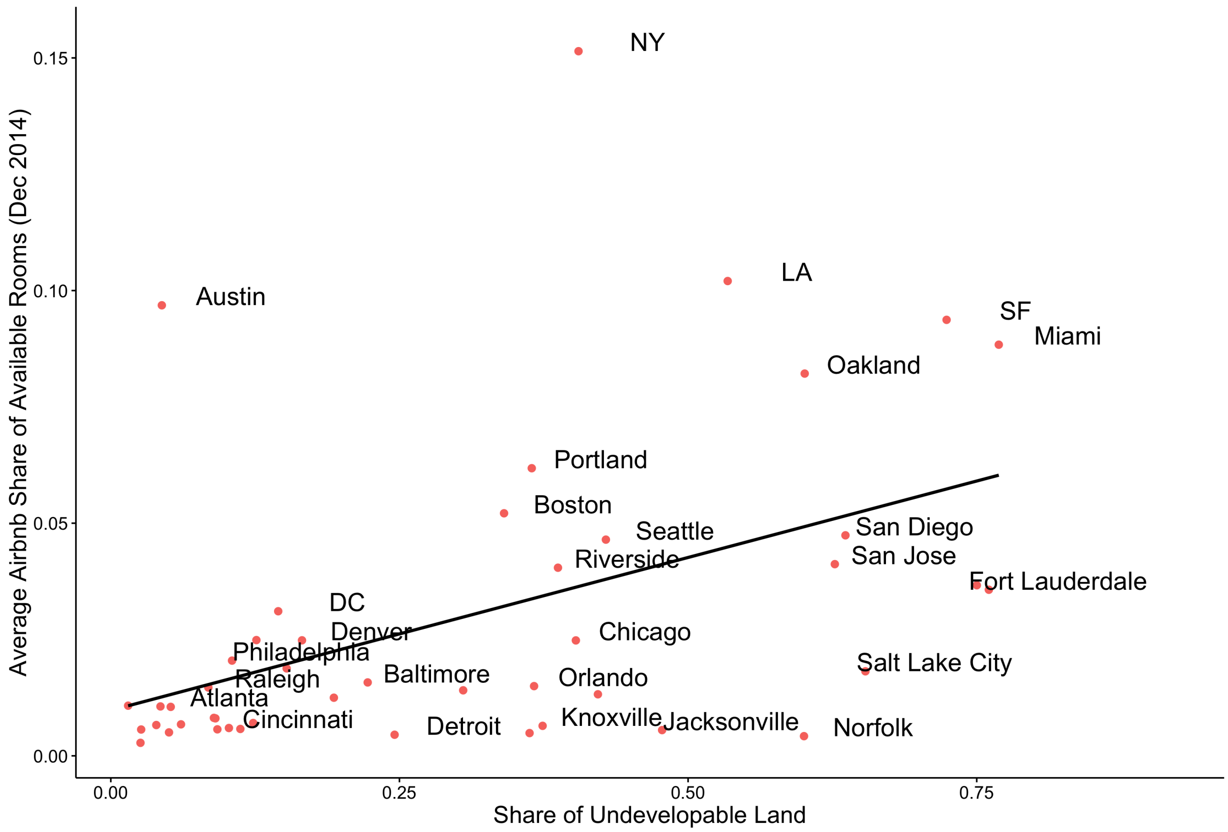
The figure plots the size of Airbnb over time in 10 selected cities. The y-axis is the daily share of Airbnb listings out of all (hotel and Airbnb) rooms available for short-term accommodation. The 10 selected cities are those with the largest number of listings on Airbnb as of December 2014 among the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

Figure 2: Peer Production and Hotel Revenues



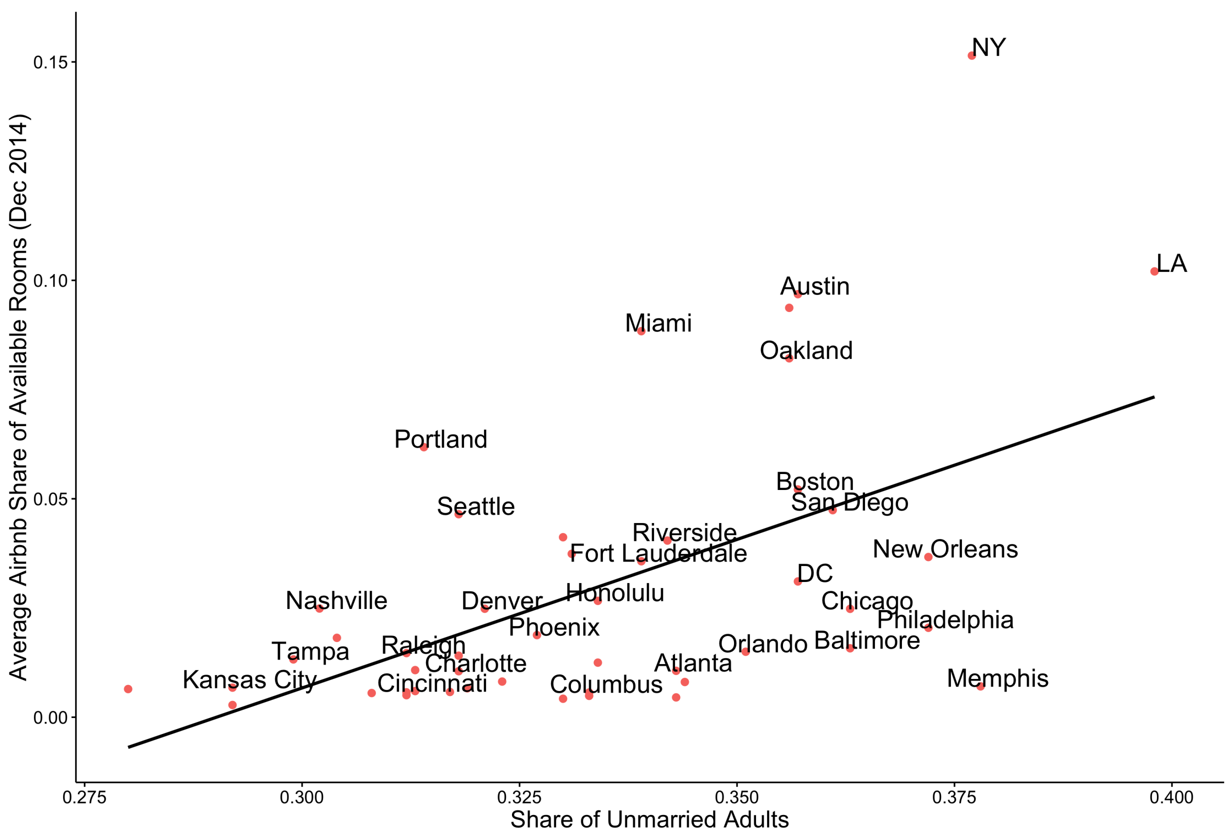
This figure plots the supply share of Airbnb against the average revenue per available room in each respective city.

Figure 3: Peer Production and Hotel Supply Constraints



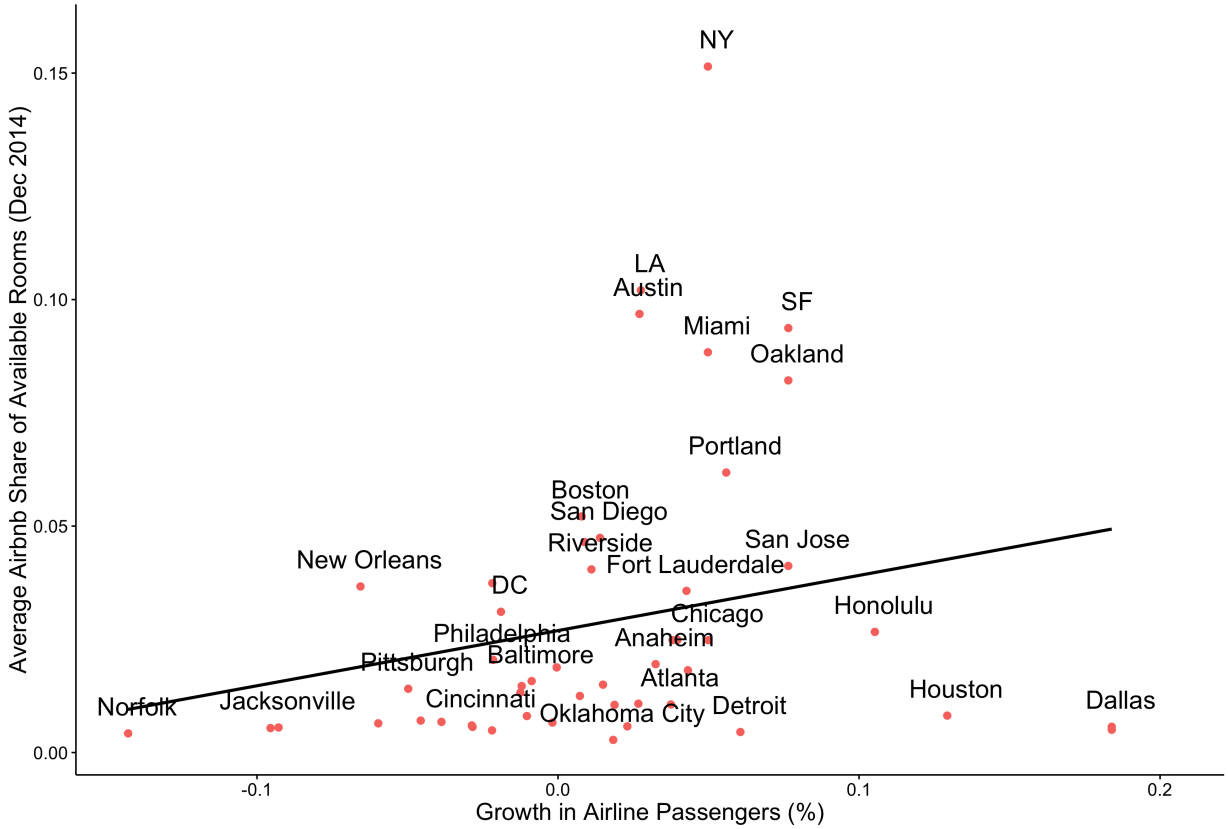
The figure plots the size of Airbnb against a proxy for the constraints to the construction of new hotels, the share of undevelopable area developed by Saiz (bottom panel). This index measures the share of a city that is undevelopable due to geographic constraints, like steep mountains or the ocean. The size of Airbnb is measured as the average share of available listings in December 2014. Figure A2 in the Appendix confirms that regulatory constraints are also good predictors of peer entry.

Figure 4: Peer Production and Peers' Costs



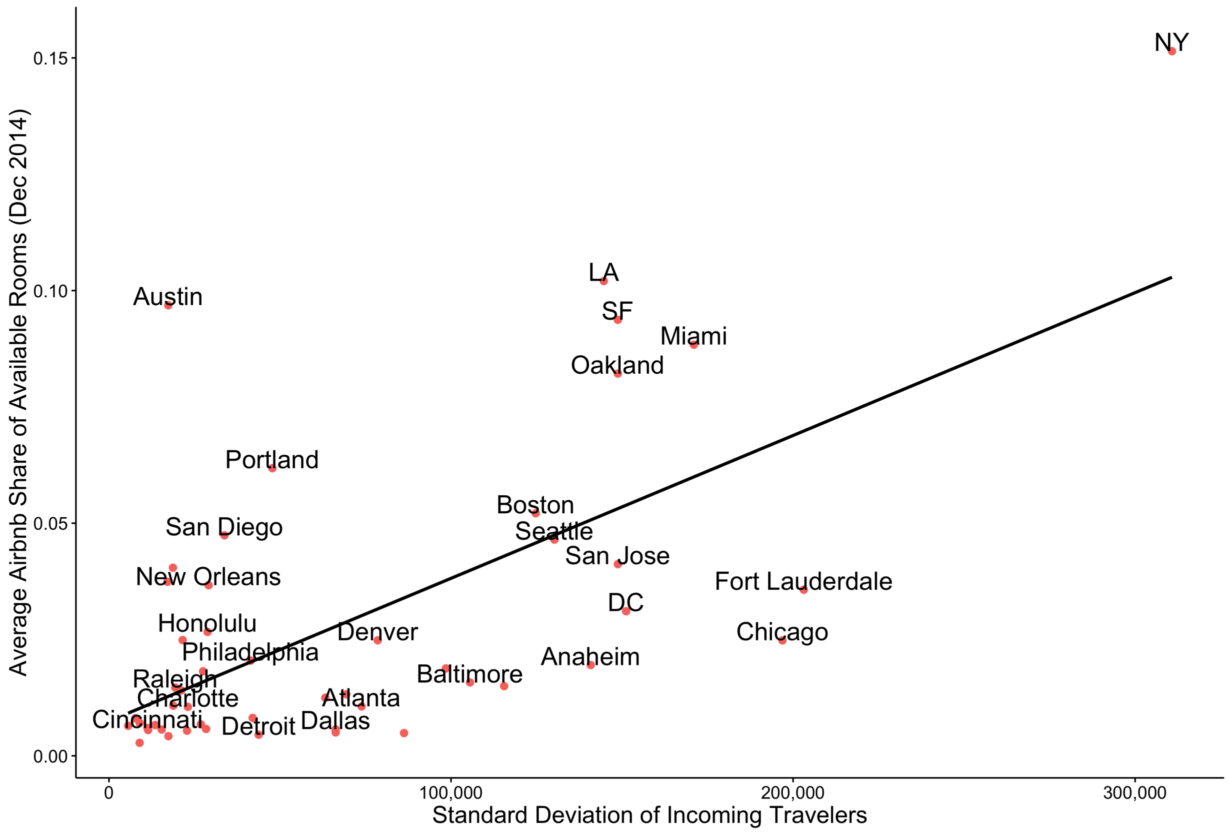
The figure plots the size of Airbnb against the share of unmarried adults in the MSA. The size of Airbnb is measured as the average share of available listings in December 2014. Figure A3 confirms that another proxy of peer costs (presence of children) is a good (negative) predictor of peer entry.

Figure 5: Peer Production and Demand Growth



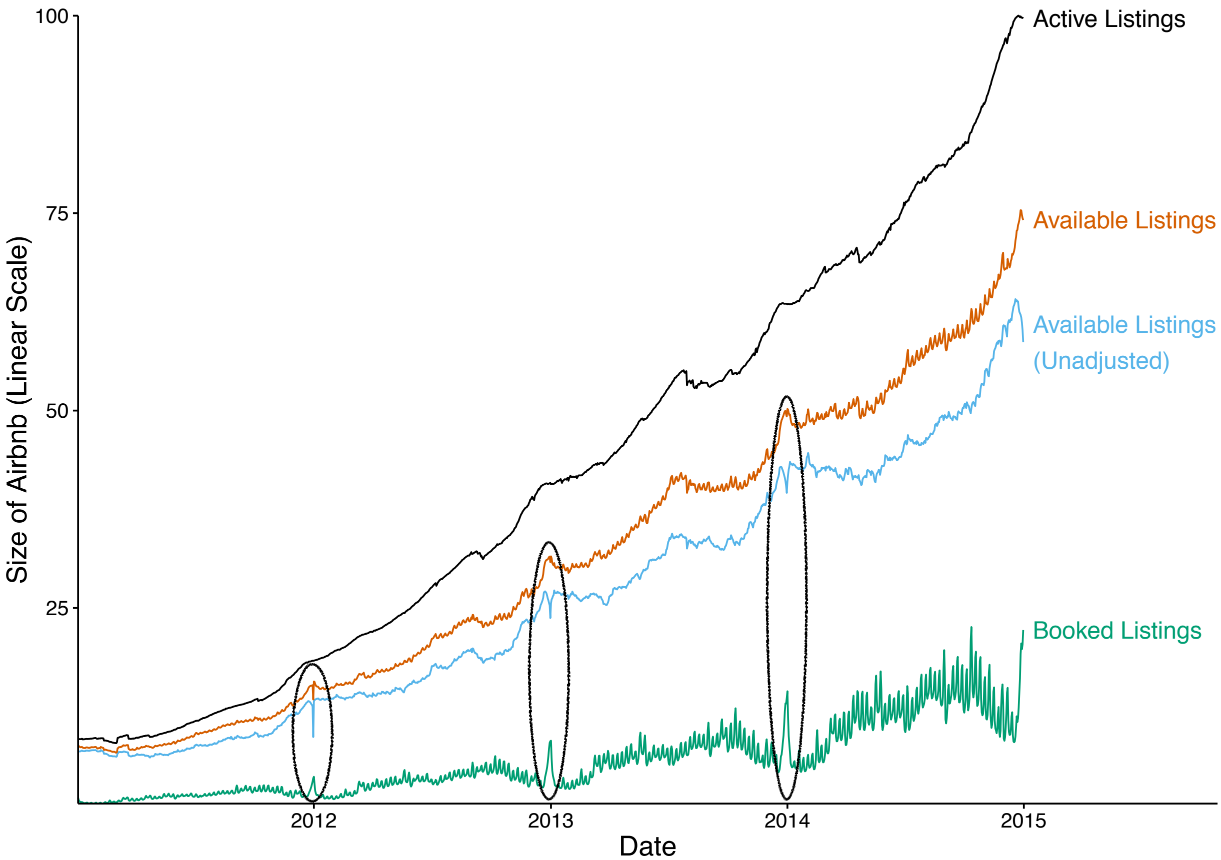
This figure plots the size of Airbnb against the growth rate in incoming air passengers to an MSA between June 2011 and June 2012. We focus on data from 2011-2012, when Airbnb was very small relative to the accommodation market, to limit the possibility the the availability of Airbnb hosts could generate such growth in demand. The size of Airbnb is measured as the average share of available listings in December 2014.

Figure 6: Peer Production and Variability of Demand



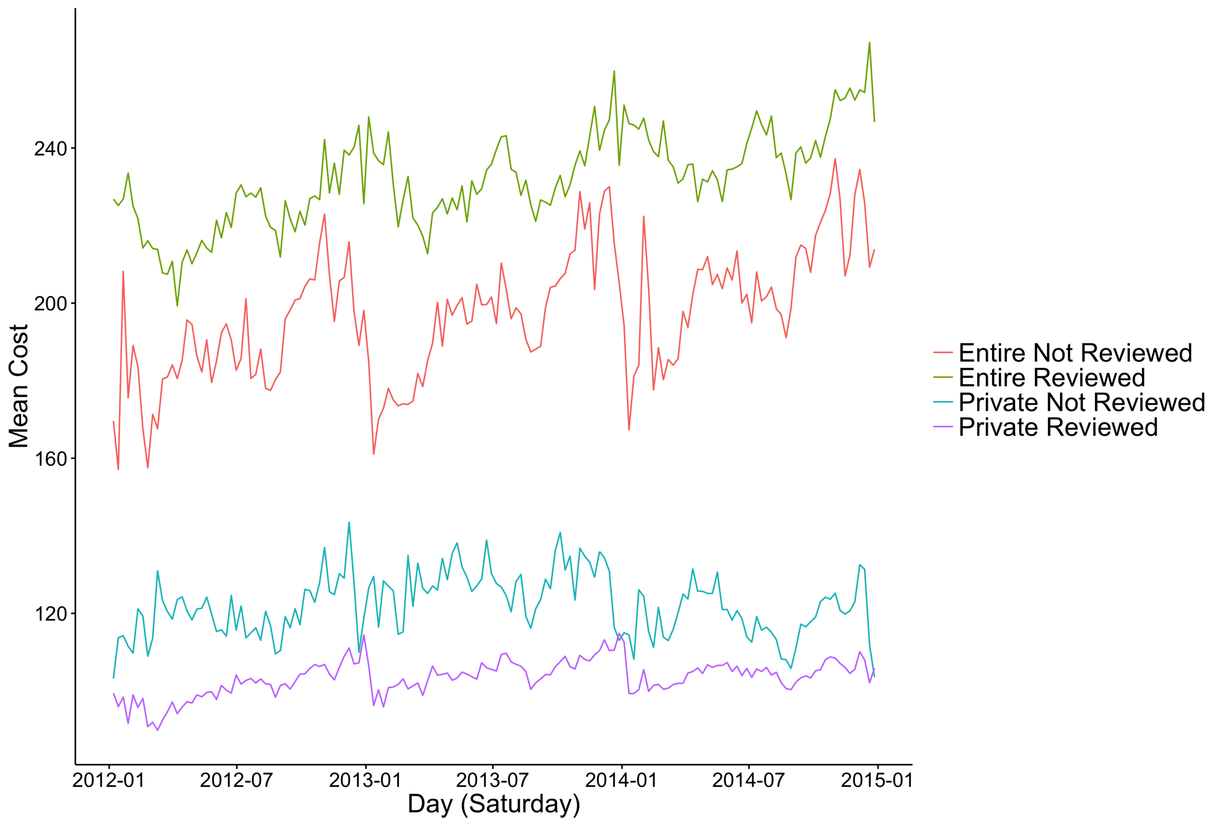
This figure plots the size of Airbnb against the standard deviation of incoming air passengers. The standard deviation of air travelers is measured using monthly data on arriving (not returning) passengers at major US airports. We focus on data from 2011, when Airbnb was very small relative to the accommodation market, to limit the possibility the the availability of Airbnb hosts could generate such variability in demand. The size of Airbnb is measured as the average share of available listings in December 2014.

Figure 7: 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 8: Mean Costs of Airbnb Hosts in New York City



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

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	0.62	0.65	0.70
Std Dev Hotel Occupancy	50	0.14	0.03	0.12	0.14	0.15
Mean Hotel Price ($)	50	108.26	33.16	87.45	97.44	121.03
Std Dev Hotel Price	50	16.25	9.11	9.81	12.90	20.93
Mean Hotel Revenue (Thousand $)	50	3,782.16	3,726.68	1,577.14	2,380.94	4,747.65
Airbnb Share of Available Rooms (Dec. 2014)	50	0.03	0.03	0.01	0.02	0.04
Airbnb Share of Potential Guests (Dec. 2014)	50	0.04	0.04	0.01	0.02	0.06
Airbnb Share of Housing Units (Dec. 2014)	50	0.001	0.001	0.0003	0.001	0.002
Mean Airbnb Occupancy	50	0.12	0.06	0.08	0.09	0.15
Std Dev Airbnb Occupancy	50	0.07	0.02	0.06	0.07	0.09
Mean Airbnb Price ($)	50	110.06	25.19	93.02	102.52	122.81
Std Dev Airbnb Price	50	31.62	13.19	22.32	28.78	35.50
Mean Price Ratio	50	1.06	0.28	0.92	1.01	1.12
Std Dev Price Ratio	50	0.33	0.17	0.21	0.30	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 monthly average of daily share of rooms in the last month of our sample, i.e. December 2014. The Airbnb share of potential guests is computed as the monthly average of rooms adjusted for their capacity, and assuming a conservative average hotel capacity of 2.5 people per room.

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	12.01	4.23	9.65	11.34	13.76
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)
Undevelopable Area	0.032*	0.025
	(0.017)	(0.016)
SD. Incoming Air Passengers (2011)	0.002**	0.001**
	(0.001)	(0.001)
% Never Married	0.378**	0.434***
	(0.155)	(0.158)
% Growth in Air Passengers (2012-2011)	0.068	0.102
	(0.066)	(0.064)
Wharton Residential Land Use Index (WRLURI)		0.008*
		(0.004)
% Children		−0.405**
		(0.189)
Constant	−0.120**	−0.011
	(0.050)	(0.063)
Observations	46	46
R^2	0.541	0.624
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 monthly average of daily share of rooms in the last month of our sample, i.e. 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. Total market size is measured as the average number of rooms available in December 2014 and is included as a control.

Table 4: The Supply Elasticity of Hotels Airbnb

	Log(Hotel Rooms Boooked)	Log(Airbnb Rooms Booked)
	(1)	(2)
log(Hotel Rooms)	0.988***	
	(0.057)	
log(Hotel Price)	1.379***	
	(0.109)	
log(Leaving Travelers)		0.193*
		(0.116)
log(Google Searches Outside)		0.177*
		(0.093)
log(Airbnb Rooms)		0.562***
		(0.071)
log(Airbnb Price)		2.461***
		(0.265)
IV	Yes	Yes
City FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Day of Week FE	Yes	Yes
Observations	73,000	66,935
R^2	0.958	0.868
Note:		Standard Errors Clustered at a City 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 log of local Google Search Trends for hotels outside of the city as additional controls. The instruments are demand-side shifters – 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)	0.955***	0.317***	0.411***
	(0.064)	(0.041)	(0.040)
log(Google Search Trend)	0.382***	0.136***	0.154***
	(0.049)	(0.020)	(0.023)
log(Available Listings)	−0.032**	−0.013**	−0.007
	(0.015)	(0.006)	(0.008)
IV	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes
Observations	73,000	73,000	73,000
R^2	0.735	0.605	0.852
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 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 C 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)	0.972***	0.359***	0.447***	1.032***	0.404***	0.343***
	(0.093)	(0.029)	(0.060)	(0.123)	(0.025)	(0.097)
log(Google Search Trend)	0.345***	0.114***	0.154***	0.496***	0.204***	0.156***
	(0.078)	(0.025)	(0.041)	(0.048)	(0.020)	(0.021)
log(Available Listings)	−0.064**	−0.018*	−0.037**	−0.042	−0.020*	−0.003
	(0.026)	(0.009)	(0.017)	(0.027)	(0.012)	(0.010)
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	33,580	33,580	33,580	33,580	33,580	33,580
R^2	0.752	0.607	0.862	0.559	0.551	0.670

Note: Standard Errors Clustered at a City 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: New York Hotel Minimum Prices

City	Hotel Type	Minimum Price ($)
New York/NY	Luxury	273.35
New York/NY	Upper Upscale	177.32
New York/NY	Upscale	140.85
New York/NY	Upper Midscale	110.76
New York/NY	Midscale	91.77
New York/NY	Economy	73.13
New York/NY	Independent	151.18

This table displays the minimum average price charged by the respective hotel types in New York. We interpret these minimum prices as the shadow marginal costs of hotels when setting prices.

Table 8: Demand Estimates

	Chicago		Las Vegas		Los Angeles		New York		San Francisco	
Parameter	Est	SD	Est	SD	Est	SD	Est	SD	Est	SD
Mean alpha	0.041	0.001	0.057	0.001	0.052	0.001	0.020	0.001	0.034	0.001
SD alpha	0.017	0.000	0.024	0.000	0.018	0.000	0.008	0.000	0.014	0.000
Luxury	-0.424	0.169	-5.199	0.521	5.609	0.116	2.538	0.154	-0.042	0.143
Upper Upscale	-0.579	0.157	-5.876	0.511	1.484	0.110	1.376	0.153	-0.498	0.139
Upscale	-2.119	0.156	-6.648	0.510	0.485	0.110	0.440	0.153	-3.251	0.139
Upper Midscale	-2.733	0.156	-7.612	0.511	-0.558	0.110	-0.373	0.153	-3.140	0.139
Midscale	-4.308	0.156	-8.469	0.510	-2.051	0.110	-2.447	0.153	-5.791	0.140
Economy	-4.576	0.156	-8.225	0.510	-2.150	0.110	-2.667	0.153	-4.957	0.139
Independent	-2.044	0.156	-3.426	0.511	1.550	0.110	1.736	0.154	-1.764	0.139
Rev. Entire Apt	-7.649	0.170	-12.077	0.551	-3.312	0.114	-3.303	0.152	-5.965	0.142
Unrev. Entire Apt	-9.484	0.178	-13.448	0.576	-4.659	0.116	-4.916	0.151	-7.541	0.143
Rev. Private Room	-10.267	0.166	-15.868	0.520	-7.430	0.113	-5.716	0.152	-8.772	0.143
Unrev. Private Room	-12.349	0.168	-17.930	0.537	-9.477	0.117	-7.542	0.152	-10.890	0.143
Time Trend (Weeks)	0.016	0.000	0.015	0.001	0.018	0.000	0.009	0.000	0.015	0.000
Airbnb Time Trend (Weeks)	0.004	0.000	0.005	0.000	0.008	0.000	0.005	0.000	0.008	0.000
Google Search Index	0.093	0.006	0.120	0.010	0.095	0.008	0.021	0.002	0.140	0.006

This table displays the demand estimates from the structural model. The data include all Saturday nights between 2011 and 2014. The Google Search Index is a normalized series of searches for hotel in the city (e.g. "hotels new york"). The unit of the time trend is weeks and it ranges between 1 and 208.

Table 9: Demand Estimates (Dollar Values)

	Chicago	Las Vegas	Los Angeles	New York	San Francisco
Parameter	Estimate (in Dollars)				
Luxury	72.28	-35.30	178.97	223.39	89.28
Upper Upscale	68.52	-47.11	99.82	165.37	75.81
Upscale	31.05	-60.57	80.64	118.66	-5.51
Upper Midscale	16.13	-77.39	60.63	78.07	-2.22
Midscale	-22.18	-92.33	31.99	-25.48	-80.53
Economy	-28.71	-88.07	30.08	-36.48	-55.87
Independent	32.88	-4.36	101.09	183.34	38.43
Rev. Entire Apt	-81.67	-138.76	39.71	-12.68	-35.03
Unrev. Entire Apt	-126.30	-162.68	13.86	-93.22	-81.57
Rev. Private Room	-145.34	-204.89	-39.31	-133.13	-117.94
Unrev. Private Room	-195.98	-240.85	-78.58	-224.33	-180.48

This table displays the demand estimates from the structural model normalized to a dollar value. The value of the outside option is 0. Each parameter represents the utility function coefficient divided by the mean of α, the price sensitivity of consumers in the sample. The data include all Saturday nights between 2011 and 2014. The Google Search Index is a normalized series of searches for hotel in the city (e.g. "hotels new york"). The unit of the time trend is weeks and it ranges between 1 and 208.

Table 10: Demand Elasticities

	Chicago	Las Vegas	LA	NY	SF
Luxury	-2.54	-2.39	-3.74	-4.47	-3.54
Upper Upscale	-1.95	-2.72	-4.44	-9.67	-3.26
Upscale	-1.72	-2.69	-4.39	-9.61	-3.48
Upper Midscale	-1.57	-2.56	-4.23	-8.85	-3.46
Midscale	-1.33	-2.34	-3.83	-7.60	-3.11
Economy	-1.01	-1.98	-3.10	-7.56	-2.75
Independent	-1.72	-1.67	-3.97	-8.47	-3.27
Entire Reviewed	-2.30	-1.72	-5.60	-9.78	-4.18
Entire Not Reviewed	-2.17	-1.90	-5.67	-9.48	-4.20
Private Reviewed	-1.41	-2.23	-3.83	-5.88	-3.08
Private Not Reviewed	-1.34	-1.98	-3.67	-5.50	-2.92

This table displays the average demand elasticities to price by city and option type.

Table 11: Demand Elasticities

NY	Luxury	Upper Up.	Upscale	Upper Mid.	Midscale	Economy	Independent	Ent. Rev.	Ent. Unrev.	Pri. Rev.	Pri. Unrev.
Luxury	-4.47	4.01	3.16	2.41	1.64	1.62	3.67	2.80	2.54	1.07	0.97
Upper Upscale	0.80	-9.67	1.62	1.53	1.33	1.33	1.63	1.57	1.54	1.08	1.02
Upscale	0.30	0.75	-9.61	0.78	0.72	0.72	0.77	0.78	0.78	0.61	0.59
Upper Midscale	0.13	0.40	0.44	-8.85	0.45	0.45	0.41	0.45	0.45	0.40	0.39
Midscale	0.02	0.06	0.07	0.08	-7.60	0.09	0.07	0.08	0.08	0.08	0.08
Economy	0.01	0.05	0.06	0.07	0.07	-7.56	0.06	0.06	0.07	0.07	0.07
Independent	1.11	2.46	2.50	2.42	2.16	2.15	-8.47	2.45	2.43	1.77	1.69
Entire Reviewed	0.03	0.08	0.08	0.08	0.08	0.08	0.08	-9.78	0.08	0.07	0.06
Entire Not Reviewed	0.00	0.02	0.02	0.02	0.02	0.02	0.02	0.02	-9.48	0.02	0.01
Private Reviewed	0.00	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.02	-5.88	0.02
Private Not Reviewed	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-5.50

This table displays the average own and cross-price demand elasticities in New York.

Table 12: Consumer Surplus from Airbnb

			Consumer Surplus				Room-Nights Booked		
		Base	No Airbnb Unconstr.	No Airbnb Constr.	No Airbnb Constr. High Demand	Base	No Airbnb Unconstr.	No Airbnb Constr.	No Airbnb Constr. High Demand
		$ Millions	% Decrease	% Decrease	% Decrease	Thousands	% Decrease	% Decrease	% Decrease
Chicago	2012	148	-0.11	-0.13	-0.17	4170	-0.07	-0.08	-0.10
Chicago	2013	153	-0.22	-0.27	-0.39	4233	-0.13	-0.16	-0.24
Chicago	2014	166	-0.39	-0.58	-0.84	4404	-0.23	-0.35	-0.54
Las Vegas	2012	168	-0.01	-0.01	-0.01	6471	-0.00	-0.00	-0.00
Las Vegas	2013	172	-0.02	-0.02	-0.02	6551	-0.01	-0.01	-0.01
Las Vegas	2014	204	-0.04	-0.05	-0.06	7128	-0.02	-0.03	-0.04
Los Angeles	2012	124	-0.24	-0.28	-0.37	4122	-0.14	-0.17	-0.23
Los Angeles	2013	133	-0.51	-0.67	-0.93	4239	-0.29	-0.41	-0.61
Los Angeles	2014	148	-1.00	-1.47	-2.16	4426	-0.53	-0.91	-1.53
New York	2012	336	-1.39	-1.93	-2.28	4756	-1.03	-1.49	-1.82
New York	2013	368	-2.18	-3.05	-3.68	5053	-1.60	-2.36	-2.96
New York	2014	413	-2.82	-4.34	-5.25	5413	-2.02	-3.38	-4.31
San Francisco	2012	103	-0.59	-0.90	-1.25	2252	-0.39	-0.64	-0.97
San Francisco	2013	115	-1.05	-1.96	-2.60	2352	-0.67	-1.45	-2.12
San Francisco	2014	120	-1.59	-2.86	-3.95	2361	-0.99	-2.06	-3.24

This table displays consumer surplus and rooms booked implied by the model for three scenarios. All calculations are for Saturday nights only. "Base" refers to the observed markets with Airbnb, "No Airbnb - 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 "No Airbnb - Constrained" imposes hotel capacity constraints. We keep hotel prices constant in both counterfactuals. The percentage change figures display the change relative to the "Base" scenario. "High Demand" refers to Saturday nights when at least one hotel type experiences occupancy in excess of 92.5%.

Table 13: Competitive Effects on Hotels

		Base	All Hotels - Bookings		
				No Airbnb	
			Unconstr.	Constr.	Opt.Prices
		Thousands	% Increase	% Increase	% Increase
Chicago	2013	4216	0.27	0.24	0.16
Chicago	2014	4370	0.53	0.41	0.29
Las Vegas	2013	6549	0.03	0.03	0.01
Las Vegas	2014	7121	0.08	0.07	-0.05
Los Angeles	2013	4196	0.75	0.63	0.47
Los Angeles	2014	4331	1.64	1.25	0.95
New York	2013	4888	1.73	0.94	0.83
New York	2014	5175	2.49	1.06	0.93
San Francisco	2013	2305	1.36	0.56	0.45
San Francisco	2014	2285	2.31	1.21	0.94

This table displays the total number of hotel rooms booked on Saturday nights by city and year according to our model estimates. The first column shows the baseline number: in LA in 2012, for example, 4.104 million rooms were booked on Saturday nights. The second, third, and fourth columns show the percentage increase in the number of hotel rooms booked in the absence of Airbnb for three different scenarios: without considering hotel capacity constraints, taking into account hotel capacity constraints, and only considering nights when at least one hotel scale hit 92.5% capacity (we define those nights as high demand days). In LA in 2012, hotels would have experienced an increase in occupancy between .32% and .28%, depending on the specific alternative scenario. In all the cities with the exception of Chicago, hotels benefit less from the absence of Airbnb in high demand days. This is because in those days all hotel scales frequently reach capacity whether Airbnb is present or not. Chicago is an exception because in high demand days typically only one or two hotel scales are capacity constrained, but other scales are able to absorb Airbnb guests.

Table 14: Airbnb Bookings: Market Expansion versus Business Stealing

		Airbnb Room-Nights Booked	Share New Bookings		
			Unconstr.	Constr.	Opt. Prices
Chicago/IL	2013	16815	0.33	0.41	1.12
Chicago/IL	2014	33112	0.30	0.46	1.01
Las Vegas/NV	2013	2219	0.20	0.24	0.82
Las Vegas/NV	2014	6557	0.18	0.28	1.96
Los Angeles/Long Beach/CA	2013	43641	0.28	0.39	0.77
Los Angeles/Long Beach/CA	2014	94764	0.25	0.43	0.57
New York/NY	2013	165102	0.49	0.72	0.81
New York/NY	2014	238063	0.46	0.77	0.81
San Francisco/San Mateo/CA	2013	47078	0.34	0.72	0.97
San Francisco/San Mateo/CA	2014	76146	0.31	0.64	0.82

This table shows the number of rooms booked on Airbnb on Saturday nights by city and year according to our model estimates. The first column shows the baseline number: in Chicago in 2012 8,094 rooms were booked on Saturday nights on Airbnb. The second and third column show the share of those bookings resulting from market expansion in two scenarios: without considering hotel capacity constraints, and taking those capacity constraints into account. Between 35 and 39% of bookings on Airbnb would have not been hotel bookings in the absence of Airbnb in Chicago in 2012.

Table 15: New York Hotel - Abb Type Costs

City	Airbnb Type	Mean Cost	SD Cost
New York/NY	Entire Reviewed	225.30	61.79
New York/NY	Entire Not Reviewed	192.05	21.57
New York/NY	Private Reviewed	100.74	18.32
New York/NY	Private Not Reviewed	120.85	26.09

This table displays the mean and standard deviations of the estimated cost distributions of Airbnb hosts of each type in New York.

Table 16: Peer Surplus (Saturday Nights)

	Avg. Surplus Per Booking			Total Surplus			Avg. Price		
	2012	2013	2014	2012	2013	2014	2012	2013	2014
Chicago	22.48	24.88	27.51	181934	418396	910823	110.73	119.35	129.34
Las Vegas	28.31	25.54	24.81	8888	56673	162666	164.86	146.34	148.21
Los Angeles	22.64	26.49	30.49	423527	1155981	2889521	117.29	130.88	144.32
New York	22.93	25.92	27.91	2250880	4279096	6645311	142.88	152.45	158.82
San Francisco	21.37	26.35	33.16	496600	1240413	2525077	129.72	148.94	167.95

This table displays the Saturday night average surplus per booking, total surplus, and average transaction price for five cities and 3 years. Surplus is calculated by taking the integral of the difference between the average transaction price and the cost costs, where costs are drawn from the estimated cost distribution for each city and listing type.

Table 17: Peer Surplus - Constraints (Saturday Nights)

		Avg. Surplus Per Night		Avg. Price	
Market	Airbnb Type	Unconstrained	Constrained	Unconstrained	Constrained
Chicago	Entire Prop. Reviewed	5007	11455	150	173
Chicago	Private Room Reviewed	1047	2832	68	79
Las Vegas	Entire Prop. Reviewed	1284	1788	192	197
Las Vegas	Private Room Reviewed	215	323	51	54
Los Angeles	Entire Prop. Reviewed	21157	29117	158	167
Los Angeles	Private Room Reviewed	2435	3573	73	78
New York	Entire Prop. Reviewed	43078	78164	179	193
New York	Private Room Reviewed	7012	13975	87	94
San Francisco	Entire Prop. Reviewed	15232	26822	184	200
San Francisco	Private Room Reviewed	2804	6195	89	101

This table displays the Saturday night average surplus per booking and average transaction price for different Airbnb types in each city during constrained and unconstrained nights. A night is considered constrained if at least on hotel type has a realized occupancy greater than 92.5%. Surplus is calculated by taking the integral of the difference between the average transaction price and the cost costs, where costs are drawn from the estimated cost distribution for each city and listing type.

A Appendix: Proof of Model Predictions

The short-run model from section 2.1 offers some comparative statics predictions. Hotel profits per available room, as well as both prices and occupancy rates, are lower if K_a is higher. In addition, for the same level of K_a, hotel profits will be reduced relatively more if their capacity constraint is often binding. This is because if demand is high relative to hotel capacity, the price equilibrium will be higher, and this will push more flexible suppliers to produce and cannibalize dedicated suppliers.

To prove the comparative statics results, let us consider the hotel profit maximization problem below:

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

Recall the equilibrium condition for flexible rooms: $Q_a^d(p_a, p_h) = K_a G(p_a)$, where $G()$ is the distribution of flexible marginal costs.

The two equilibrium variables, p_h and p_a are both functions of the two capacity constraints K_h and K_a. 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:

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

We now show that the first term is zero if hotel capacity is not binding and negative otherwise, while the second term is always negative. This is because both prices are a decreasing function of flexible capacity, and hotel profits are an increasing function of flexible price, and of own price if hotel capacity is binding.

Let's first consider the case where the hotel capacity constraint does not bind. By the FOC, $\frac{\partial \Pi_h}{\partial p_h} = 0$. Also, the hotel profits are an increasing function of p_a since $\frac{\partial \Pi_h}{\partial p_a} = \frac{\partial Q_h^d}{\partial p_a}(p_h - c_h) \geq 0$. By totally differentiating the system of equilibrium equations $Q_h^d = -\frac{\partial Q_h^d}{\partial p_h}(p_h - c)$ and $Q_a^d = K_a G(p_a)$, we obtain $\frac{dp_a}{dK_a} = \frac{\left[2\frac{\partial Q_h}{\partial p_h} + \frac{\partial^2 Q_h}{\partial p_h^2}(p_h - c_h)\right]G(p_a)}{\left[2\frac{\partial Q_h}{\partial p_h} + \frac{\partial^2 Q_h}{\partial p_h^2}(p_h - c_h)\right]\left[\frac{\partial Q_a}{\partial p_a} - K_a g(p_a)\right] - \frac{\partial Q_a}{\partial p_h}\left[\frac{\partial Q_h}{\partial p_a} + \frac{\partial^2 Q_h}{\partial p_h \partial p_a}(p_h - c_h)\right]}$, which is negative. This results from the numerator being negative since the second derivative of the hotel profit maximization function is negative for an interior maximum. The denominator is instead positive since the first term is the product of two negative terms, and the second term to be subtracted is positive but smaller than the first term in absolute value. Indeed, $-\frac{\partial Q_a}{\partial p_a} + K_a g(p_a) \geq \frac{\partial Q_h}{\partial p_a} \geq 0$ 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, $\frac{\partial Q_i}{\partial p_j} \leq$

$-\frac{\partial Q_j}{\partial p_j} = \frac{\partial Q_i}{\partial p_j} + \frac{\partial Q_0}{\partial p_j}$. In addition, $-\left[2\frac{\partial Q_h}{\partial p_h} + \frac{\partial^2 Q_h}{\partial p_h^2}(p_h - c_h)\right] \geq \left[\frac{\partial Q_h}{\partial p_a} + \frac{\partial^2 Q_h}{\partial p_h \partial p_a}(p_h - c_h)\right] \geq 0$ as long as the Bertrand price equilibrium is stable and hotel optimal prices are an increasing function of competitors' prices (Bulow et al. (1985)).

Now we consider the case where the hotel capacity constraint binds. Here the two equilibrium equations are $Q_h = K_h$ and $Q_a = K_a G(p_a)$. Since we are at a constrained maximum $\frac{\partial \Pi_h}{\partial p_h} > 0$, while $\frac{\partial \Pi_h}{\partial p_a} \geq 0$ as before. Now $\frac{dp_h}{dK_a} = \frac{-\frac{\partial Q_h}{\partial p_a} G(p_a)}{\frac{\partial Q_h}{\partial p_h}\left[\frac{\partial Q_a}{\partial p_a} - K_a g(p_a)\right] - \frac{\partial Q_a}{\partial p_h}\frac{\partial Q_h}{\partial p_a}}$ and $\frac{dp_a}{dK_a} = \frac{\frac{\partial Q_h}{\partial p_h} G(p_a)}{\frac{\partial Q_h}{\partial p_h}\left[\frac{\partial Q_a}{\partial p_a} - K_a g(p_a)\right] - \frac{\partial Q_a}{\partial p_h}\frac{\partial Q_h}{\partial p_a}}$. Both numerators are negative, and they have the same positive denominator. The denominator is positive because the first term is the product of two negative terms, each of which is bigger in absolute value than a factor of the second term. This is again due to the fact that the effect of a price change on own demand is bigger than on the demand for the other product, $-\frac{\partial Q_i}{\partial p_i} \geq \frac{\partial Q_j}{\partial p_i}$. 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.

The reduction in hotel profits due to flexible capacity is higher when hotel capacity is lower. Intuitively, if K_h is low the hotel capacity constraint binds more often, which will drive both flexible and dedicated room prices to be higher. Higher prices in turn will push relatively more flexible sellers to host, and this further decreases hotel profits per available room. To prove it, we show that the derivative of hotels' profit function with respect to flexible capacity is larger in absolute value when hotels are capacity-constrained.

When hotels are capacity-constrained $\frac{d\Pi_h}{dK_a} = \frac{\partial \Pi_h}{\partial p_h}\frac{dp_h}{dK_a} + \frac{\partial \Pi_h}{\partial p_a}\frac{dp_a}{dK_a}$. We showed above that both summation terms are negative and that the second is $\left[\frac{\partial \Pi_h}{\partial p_a}\frac{dp_a}{dK_a}\right]^{constr} = \frac{\frac{\partial Q_h}{\partial p_a}(p_h - c_c)\frac{\partial Q_h}{\partial p_h} G(p_a)}{\frac{\partial Q_h}{\partial p_h}\left[\frac{\partial Q_a}{\partial p_a} - K_a g(p_a)\right] - \frac{\partial Q_a}{\partial p_h}\frac{\partial Q_h}{\partial p_a}}$. When hotels are not capacity constrained, the first summation term is zero while the second term is $\left[\frac{\partial \Pi_h}{\partial p_a}\frac{dp_a}{dK_a}\right]^{unconstr} = \frac{\frac{\partial Q_h}{\partial p_a}(p_h - c_h)\frac{\partial^2 \Pi_h}{\partial p_h^2} G(p_a)}{\frac{\partial^2 \Pi_h}{\partial p_h^2}\left[\frac{\partial Q_a}{\partial p_a} - K_a g(p_a)\right] - \frac{\partial Q_a}{\partial p_h}\frac{\partial^2 \Pi_h}{\partial p_h \partial p_a}}$. After some algebra, it's easy to show that $\left[\frac{\partial \Pi_h}{\partial p_a}\frac{dp_a}{dK_a}\right]^{constr} \leq \left[\frac{\partial \Pi_h}{\partial p_a}\frac{dp_a}{dK_a}\right]^{unconstr}$ (both negative) if and only if $\left[\frac{\partial p_h}{\partial p_a}\right]^{constr} \geq \left[\frac{\partial p_h}{\partial p_a}\right]^{constr}$ (both positive), where the partial derivatives come from applying the implicit function theorem on the hotel equilibrium condition ($Q_h = K_h$ if hotels are constrained, and $Q_h = \frac{\partial Q_h}{\partial p_h}(p_h - c_h)$ otherwise). This simply means that if hotel prices are affected more by competitors' prices when hotels are capacity constrained, then the reduction in hotel profits due to an increase in flexible capacity is larger if hotel capacity constraints are more often binding.

The same condition obtained from the two alternative hotel equilibrium conditions, that $\left[\frac{\partial p_h}{\partial p_a}\right]^{constr} \geq \left[\frac{\partial p_h}{\partial p_a}\right]^{constr}$, also implies that the effect of flexible capacity on hotel occupancy will be higher and the effect on hotel prices will be lower when hotels are not capacity constrained. Intuitively, this occurs because when hotels are capacity constrained, their supply curve is vertical, and the increase in flexible capacity affects hotels through a reduction in their residual demand. A marginal downward shift in residual demand will have no effect on quantity and a large effect on price if supply is perfectly inelastic.

Analytically, the reduction in hotel occupancy is higher when hotels are not capacity constrained because $\left[\frac{dQ_h}{dK_a}\right]^{constr} = 0$ and, under that condition, $\left[\frac{dQ_h}{dK_a}\right]^{unconstr} = \frac{\partial Q_h}{\partial p_h}\frac{dp_h}{dK_a} + \frac{\partial Q_h}{\partial p_a}\frac{dp_a}{dK_a} \leq 0$. For this result, recall that in an unconstrained equilibrium, $\frac{dp_h}{dK_a} = \frac{-G(p_a)\frac{\partial^2\Pi_h}{\partial p_h \partial p_a}}{\frac{\partial^2\Pi_h}{\partial p_h^2}\left[\frac{\partial Q_a}{\partial p_a} - K_a g(p_a)\right] - \frac{\partial Q_a}{\partial p_h}\frac{\partial^2\Pi_h}{\partial p_h \partial p_a}}$ and $\frac{dp_a}{dK_a} = \frac{G(p_a)\frac{\partial^2\Pi_h}{\partial p_h^2}}{\frac{\partial^2\Pi_h}{\partial p_h^2}\left[\frac{\partial Q_a}{\partial p_a} - K_a g(p_a)\right] - \frac{\partial Q_a}{\partial p_h}\frac{\partial^2\Pi_h}{\partial p_h \partial p_a}}$. The reduction in hotel prices is higher when hotels are capacity constrained because $\left[\frac{dp_h}{dK_a}\right]^{constr} \geq \left[\frac{dp_h}{dK_a}\right]^{unconstr}$ (both negative). For this result $\left[\frac{dp_h}{dK_a}\right]^{unconstr} = \frac{-G(p_a)\frac{\partial^2\Pi_h}{\partial p_h \partial p_a}}{\frac{\partial^2\Pi_h}{\partial p_h^2}\left[\frac{\partial Q_a}{\partial p_a} - K_a g(p_a)\right] - \frac{\partial Q_a}{\partial p_h}\frac{\partial^2\Pi_h}{\partial p_h \partial p_a}}$ and $\left[\frac{dp_h}{dK_a}\right]^{constr} = \frac{-\frac{\partial Q_h}{\partial p_a}G(p_a)}{\frac{\partial Q_h}{\partial p_h}\left[\frac{\partial Q_a}{\partial p_a} - K_a g(p_a)\right] - \frac{\partial Q_a}{\partial p_h}\frac{\partial Q_h}{\partial p_a}}$.

We now prove that entry of flexible sellers is larger if the distribution of c decreases in the FOSD sense, if K_h is low, if $F(d)$ increases in the FOSD sense or becomes more variable (with a mean-preserving spread). 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.

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.

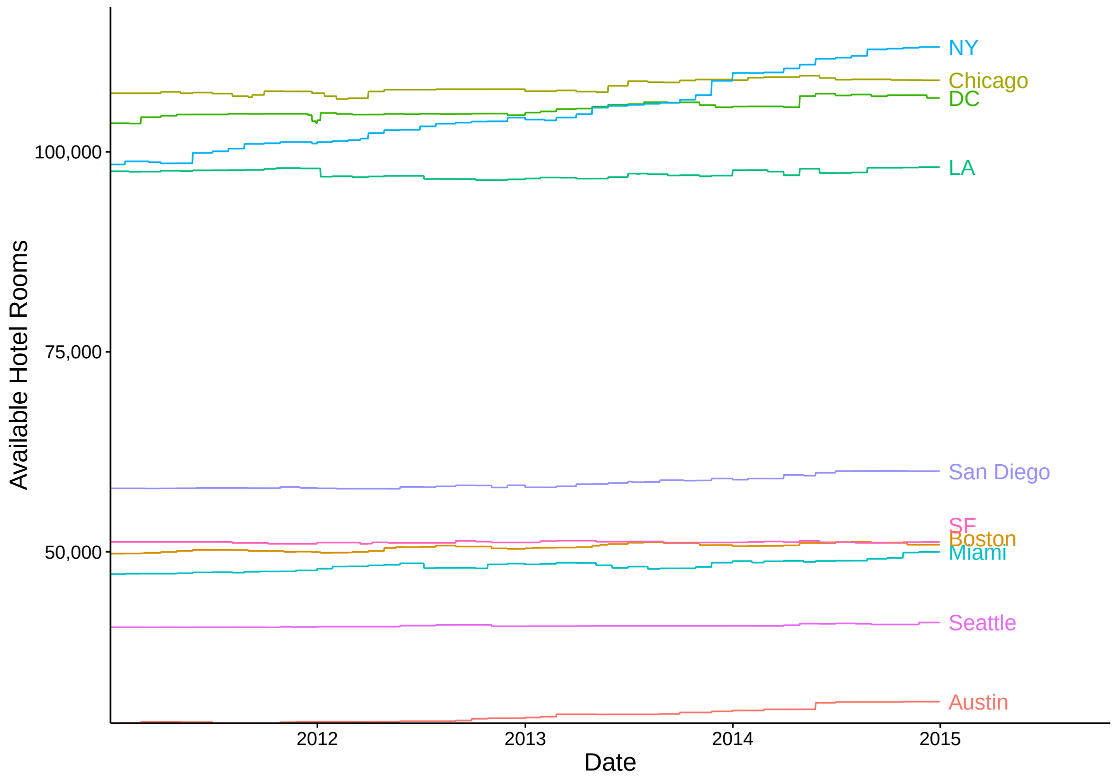
It is also straightforward to see that if $F(d)$ shifts to the right, $E_c\left[max\{0, p_a^d - c\}\right]$ will not change for any demand state, but higher demand states are more likely so v_a increases, inducing more flexible entry.

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 $Q_a^d(p_a, p_h) = K_a G(p_a)$. We proved above 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 $Q_a^d = K_a G(p_a)$ 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 $-\frac{\frac{\partial(\partial \Pi_h^d/\partial p_h)}{\partial p_a}}{\frac{\partial(\partial \Pi_h^d/\partial p_h)}{\partial p_h}} \in (0,1)$ (equilibrium stability and strategic complementarity of hotel and flexible prices) and $-\frac{\frac{\partial(\partial \Pi_h^d/\partial p_h)}{\partial d}}{\frac{\partial(\partial \Pi_h^d/\partial p_h)}{\partial p_h}} \geq 0$ (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.

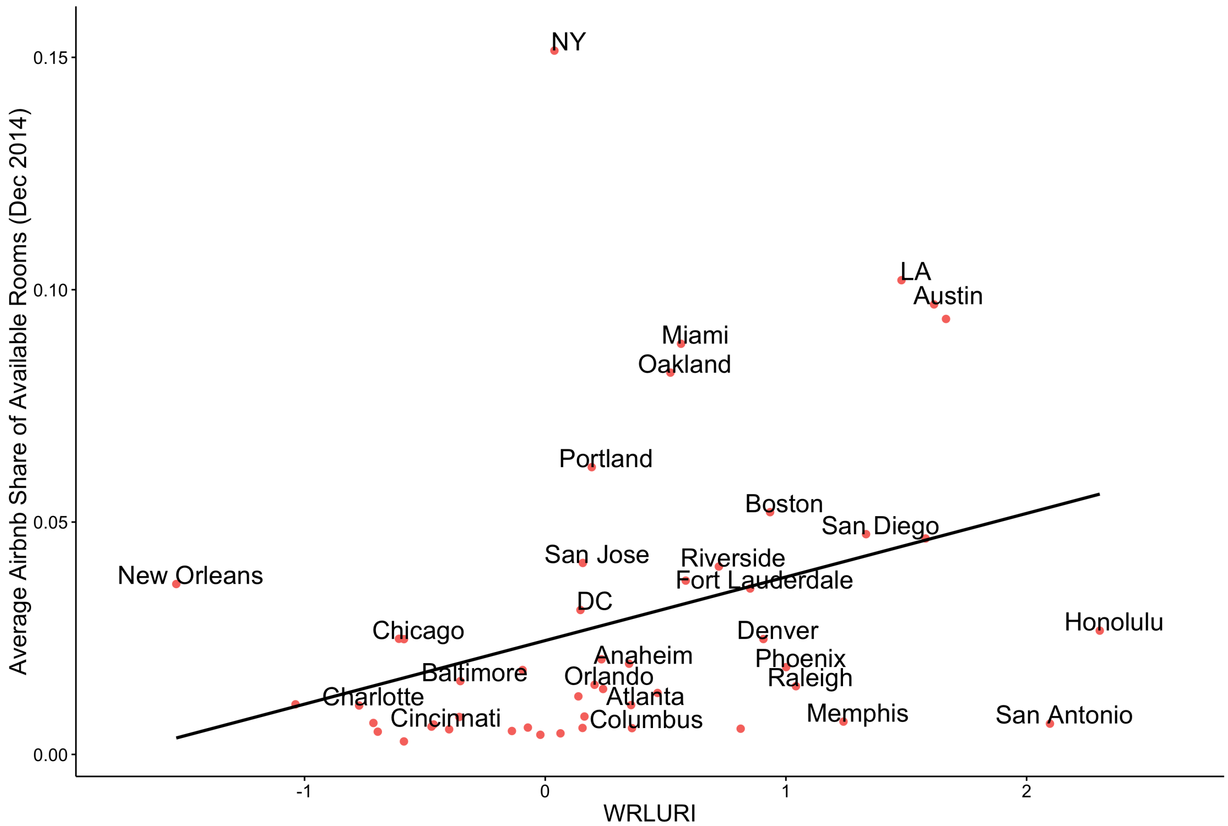
B Appendix: Other Tables and Figures

Figure A1: Hotel Rooms



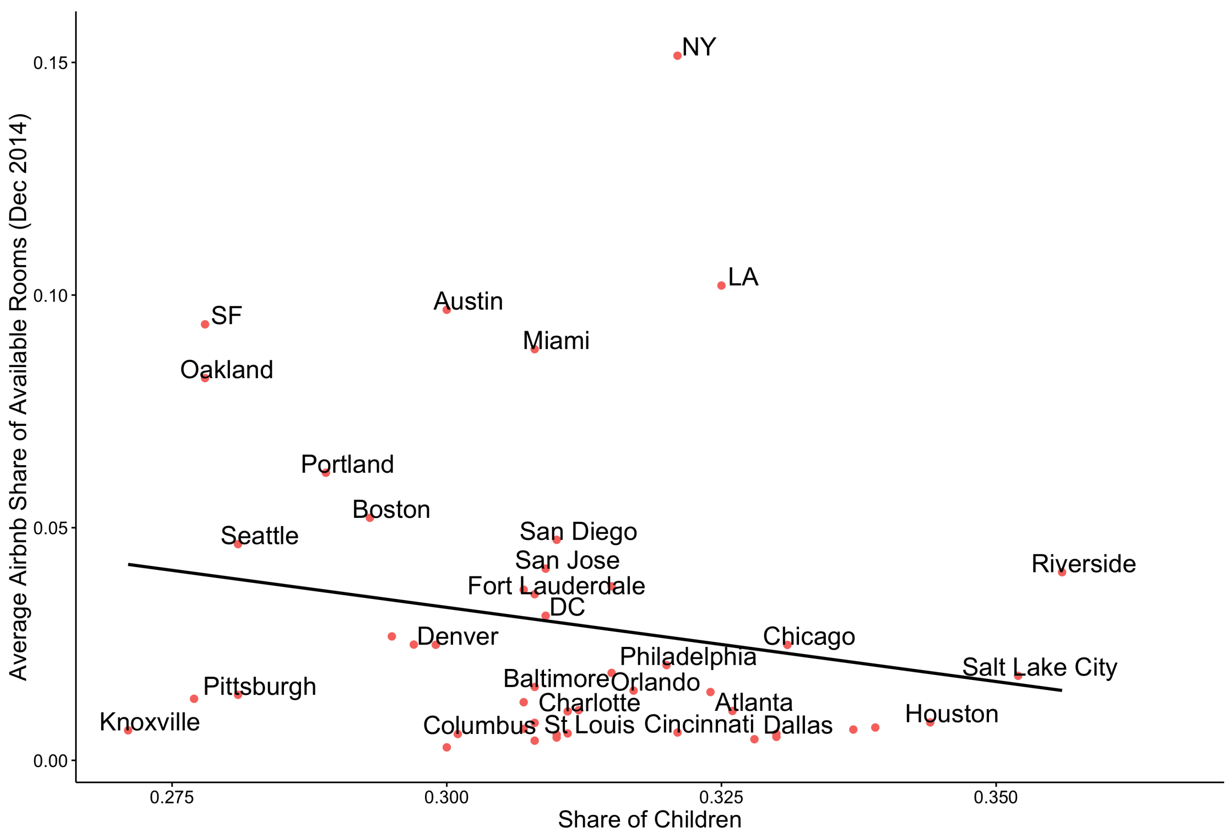
The figure plots the number of available hotel rooms over time for the top 10 cities. In contrast to the growth of Airbnb, the number of hotel rooms has been relatively stable over this time period.

Figure A2: Peer Production and Hotel Supply Constraints: WRLURI



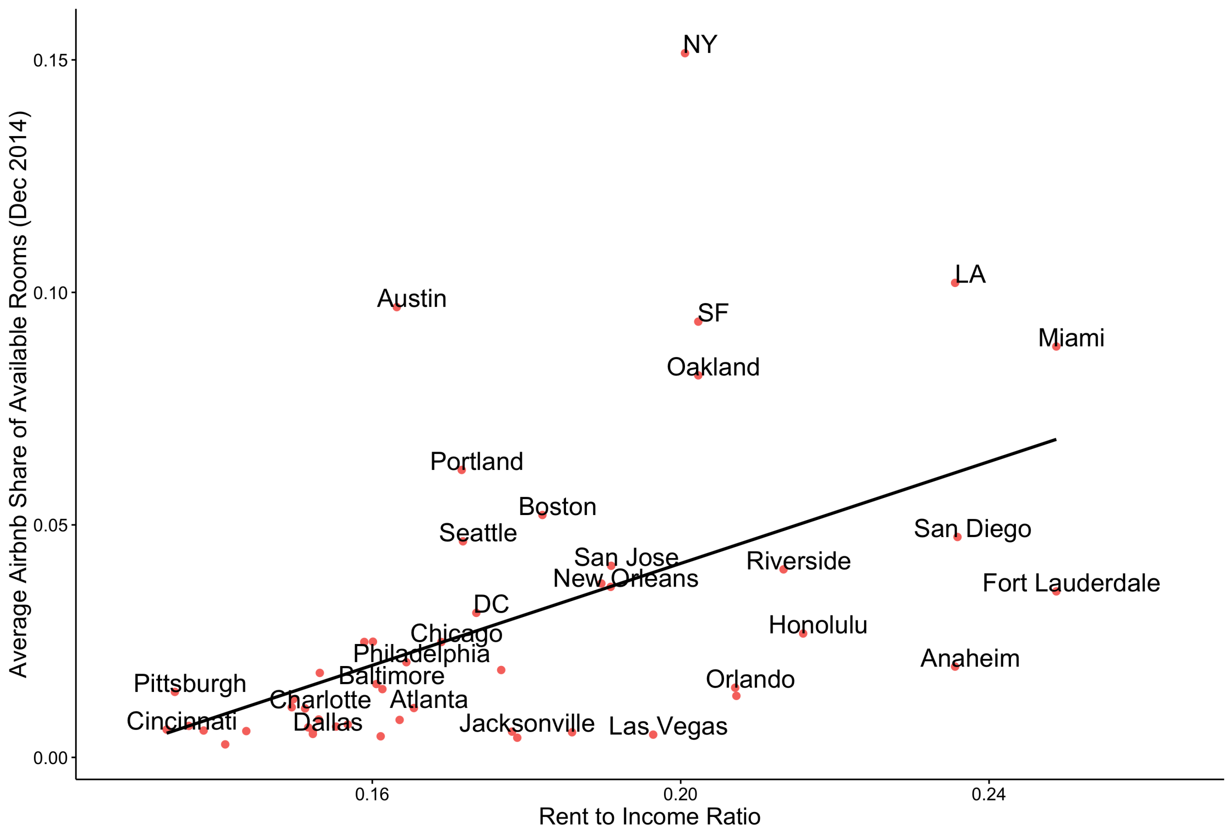
The figure is analogous to Figure 3. It plots the size of Airbnb against a measure of constraints to the construction of new hotels: the Wharton Residential Land Use Regulation Index. The index measures how stringent the local regulatory environment is in the housing market, which we consider to be similar for commercial buildings. The size of Airbnb is measured as the average share of available listings in December 2014.

Figure A3: Peer Production and Peers' Costs: Children



The figure is analogous to Figure 4 and plots the size of Airbnb against the share of children in the MSA. The size of Airbnb is measured as the average share of available listings in December 2014.

Figure A4: Peer Production and Housing Costs



The 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 December 2014.

Table A1: Heterogeneous Effects of Airbnb: Hotel Scale

	Log(RevPAR)				
	(1)	(2)	(3)	(4)	(5)
log(Incoming Air Passengers)	1.109***	0.930***	0.959***	0.848***	1.004***
	(0.163)	(0.062)	(0.081)	(0.060)	(0.080)
log(Google Search Trend)	0.657***	0.349***	0.387***	0.346***	0.412***
	(0.090)	(0.052)	(0.050)	(0.048)	(0.062)
log(Available Listings)	−0.046	−0.044**	−0.029	−0.021	0.010
	(0.046)	(0.018)	(0.019)	(0.018)	(0.023)
Hotel Scale	Luxury	Upscale	Midscale	Economy	Independent
Instruments			City Time Trends		
City FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Observations	25,857	72,998	73,000	72,058	57,912
R^2	0.576	0.584	0.708	0.852	0.771
Note:			Standard Errors Clustered at a City Level		

The table shows the IV estimates of equation 4 split by the type of hotel. Airbnb is typically considered a competitor to lower-end hotel rooms. However the data on average Airbnb prices and hotels seem to paint a slightly different picture (see Table 1). This is because the supply on Airbnb is diverse, ranging from couches in shared rooms to luxury apartments. Therefore, Airbnb can have effects across different types of hotels. The table displays our regression results across hotel scales, including luxury through economy and independent hotels (independent hotels are defined as those that do not belong to any chain regardless of their quality). The effects are negative across all scales other than independent, but are only statistically significant in the case of upscale and midscale hotels. The estimates of the effects on luxury and independent hotels are less precise due to the fact that not all cities have these hotel types and therefore there are fewer observations.

Table A2: Heterogeneous Effects of Airbnb: Room Type

	Log(RevPAR)
log(Incoming Air Passengers)	0.962***
	(0.065)
log(Google Search Trend)	0.381***
	(0.049)
log(Entire Apartments)	−0.065***
	(0.020)
log(Private Rooms)	0.016
	(0.020)
IV	Yes
City FE	Yes
Year-Quarter FE	Yes
Day of Week FE	Yes
Observations	73,000
R^2	0.734
Note:	Standard Errors Clustered at a City Level

The table shows the IV estimates of equation 4 with the effect of Airbnb split out by listing type (private rooms and entire properties). Here we investigate whether the effects of Airbnb differ by room type. We differentiate between two types: private rooms within larger homes, and entire properties. Private rooms tend to be smaller, cheaper, and suited towards small travel parties. On the other hand, entire properties are typically larger and perceived as a safer and more private travel experience. The estimates show that only entire apartments have a negative effect on hotel revenues: a doubling of private rooms on Airbnb reduces hotel revenues by 6.6%.

C Appendix: Endogeneity Concerns

This Appendix presents evidence validating our baseline specification in equation 4 against endogeneity concerns. First, in Table A3 we progressively add controls from a simple regression of hotel revenue on the size of Airbnb and other out-of-sample hotels. Our baseline specification is in the last column. The coefficients of both Airbnb listings and other hotel rooms decrease as we keep adding controls for demand fluctuations, days of the weeks, evolution over time, and market-specific seasonality. In the last two columns the coefficients do not differ in magnitude, providing some evidence that what is left to the error term might be uncorrelated with the size of Airbnb and other hotels.

Table A4 shows IV estimates of equation 4, where we use the lagged number of Airbnb listings as instruments for the current size of Airbnb. The idea behind this strategy is that due to the increasing awareness of Airbnb, the number of rooms grows over time. However, the lagged value of available rooms should not be correlated with time specific demand shocks. The estimates from this specification are slightly smaller in magnitude and statistically non-significantly different from zero.

Appendix Table A4 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 and statistically insignificant 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 countercyclical: 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 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 A5 displays the full set of results described in the previous paragraph but with the measure of Airbnb instrumented with the 30-day lag of adjusted available listings. Using this strategy, the effect of Airbnb is similar regardless of the measure used. Furthermore, the coefficient on booked listings is now -.18, which is negative as we would expect, and about 5 times as large as the coefficient on available listings (-.04). Since on average 1 out of 8 rooms is booked on Airbnb, the coefficient estimates seem broadly consistent with the booking probability.

Table A3: Hotel Revenue and Airbnb - Adding Controls

	Log(Revenue per Available Hotel Room)					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Available Listings)	0.180***	0.127***	0.127***	0.146***	−0.018	−0.038
	(0.019)	(0.018)	(0.018)	(0.028)	(0.016)	(0.024)
log(Google Trend)		0.488***	0.488***	0.413***	0.437***	0.429***
		(0.092)	(0.092)	(0.108)	(0.074)	(0.075)
log(Incoming Air Passengers)		0.098***	0.098***	0.081**	0.972***	0.994***
		(0.030)	(0.030)	(0.036)	(0.079)	(0.085)
Day of Week FE	No	No	Yes	Yes	Yes	Yes
Month-Year FE	No	No	No	Yes	Yes	Yes
Market FE	No	No	No	No	Yes	Yes
Market-Specific Time Trends	No	No	No	No	No	Yes
Observations	73,000	73,000	73,000	73,000	73,000	73,000
R^2	0.305	0.429	0.494	0.542	0.760	0.762

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. This result is robust to an instrumental variable approach (Table A4).

Table A4: Hotel Revenue and Airbnb - Different Measures of Airbnb

	Log(Revenue per Available Hotel Room)			
	(1)	(2)	(3)	(4)
log(Active Listings)	-0.011			
	(0.015)			
log(Available Listings Raw)		-0.107^{***}		
		(0.034)		
log(Available Listings Corrected)			-0.038	
			(0.024)	
log(Booked Listings)				0.122^{***}
				(0.015)
log(Google Trend)	0.431^{***}	0.420^{***}	0.429^{***}	0.395^{***}
	(0.075)	(0.074)	(0.075)	(0.071)
log(Incoming Air Passengers)	0.996^{***}	0.971^{***}	0.994^{***}	0.824^{***}
	(0.086)	(0.083)	(0.085)	(0.063)
Day of Week FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Market-Specific Time Trends	Yes	Yes	Yes	Yes
Observations	73,000	73,000	73,000	73,000
R^2	0.762	0.764	0.762	0.772
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 A5: Hotel Revenue and Airbnb - IV Estimates for Different Measures of Airbnb

	Log(Revenue per Available Hotel Room)			
	(1)	(2)	(3)	(4)
log(Google Trend)	0.434***	0.430***	0.432***	0.502***
	(0.074)	(0.074)	(0.074)	(0.088)
log(Incoming Air Passengers)	0.996***	0.983***	0.991***	1.307***
	(0.084)	(0.083)	(0.084)	(0.239)
log(Active Listings)	−0.046**			
	(0.023)			
log(Available Listings Raw)		−0.045**		
		(0.022)		
log(Available Listings Corrected)			−0.047**	
			(0.023)	
log(Booked Listings)				−0.213
				(0.130)
Day of Week FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Market-Specific Time Trends	Yes	Yes	Yes	Yes
Observations	71,519	71,519	71,519	71,519
R^2	0.760	0.761	0.760	0.692
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 A4: active listings, available listings adjusted for demand-induced calendar updates, available listings, and booked listings.