The Welfare Effects of Peer Entry: The Case of Airbnb and the Accommodation Industry

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We study the welfare effects of enabling peer supply through Airbnb in the accommodation industry. We present a model of competition between flexible and dedicated sellers - peer hosts and hotels - who provide differentiated products. We estimate this model using data from major US cities and quantify the welfare effects of Airbnb on travelers, hosts, and hotels. The welfare gains are concentrated in specific locations (New York) and times (New Year's) when hotel capacity is constrained. This occurs because peer hosts are responsive to market conditions, expand supply as hotels fill up, and keep hotel prices down as a result.
JEL: D4, K2, L1, L83, L86.
Keywords: Peer-to-Peer Platforms, Flexible Supply, Market Structure, Consumer Welfare.

I. Introduction

The Internet has greatly reduced entry and advertising costs across a variety of industries. As an example, peer-to-peer marketplaces such as Airbnb, Uber, and Etsy currently provide a platform for small and part-time *peer* providers to sell their goods and services. Several of these marketplaces have grown quickly and become widely known brands. In this paper, we study the welfare effects of peer production in the market for short-term accommodations, where Airbnb is the main peer-to-peer platform and hotels are incumbent suppliers.

Since its founding in 2008, Airbnb has grown to list more rooms than any hotel group in the world. Yet Airbnb's expansion across cities and over time has been highly heterogeneous, with supply shares ranging from over 15% to less than 1% across major US cities at the end of 2015. Airbnb's entry has also prompted policy discussions and a variety of regulatory frameworks in many places around

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the globe. In order to understand Airbnb's growth and its welfare effects, we present stylized facts about Airbnb's room supply and its effects on hotels, which we use to motivate a demand and supply framework where accommodations can be provided by either dedicated or flexible supply – hotels vs. peer hosts. A key difference between hotels and peer hosts is that while hotels have dedicated rooms that are always available for booking, peer hosts have alternative uses for their rooms, which make them more responsive to demand and price fluctuations.

We estimate our model of competition between incumbent hotels and peer hosts using data from top US cities to quantify the welfare effects of peer entry on travelers, incumbent hotels, and peer hosts. We find that in 2014, Airbnb generated \$305 million in consumer surplus, or about \$70 per Airbnb room-night booked, and \$112 million in peer host surplus, or about \$26 per room-night. The \$70 in consumer surplus per Airbnb room-night is almost equally split between the benefits from increased consumer choice and those from lower prices paid by hotel guests. These benefits came at the expense of hotels, who experienced a 1.6% decrease in revenues and a decrease in variable profits of up to 2.8%. These effects were concentrated in particular locations (e.g., New York) and times (e.g., New Year's Eve) when hotel capacity was constrained.

Our data mainly come from two sources: proprietary data from Airbnb and data from Smith Travel Research (STR), which tracks supply and demand metrics for the hotel industry. We obtain data on average prices, rooms sold, and rooms available at the city and day levels, as well as by accommodation type (four tiers, from luxury through economy), between 2011 and 2015 for the 50 largest US cities.[1] There is substantial heterogeneity in the size of Airbnb across cities and over time as measured by the Airbnb supply share, which we define as the number of available Airbnb rooms divided by the sum of rooms available from both hotels and Airbnb. Airbnb has grown more quickly in cities like New York and Los Angeles, reaching supply shares exceeding 15% and 11% respectively in 2015, while cities like St. Louis and Detroit have grown more slowly, with supply shares of less than 1% at the end of 2015. In all cities, the number of available rooms is higher during peak travel times such as Christmas and summer. This geographic and temporal heterogeneity suggests that hosts flexibly choose when to list their rooms on Airbnb, and are more likely to do so in cities and times when the returns to hosting are highest.

In Section II, we offer additional stylized facts on differences in Airbnb supply across cities and over time. Across cities, we show that the Airbnb supply share is larger in cities where hotel prices are higher. These high prices are associated with the difficulty of expanding hotel room capacity due to regulatory or geographic constraints. Airbnb supply is also larger in cities where residents tend to be single and have no children. The costs of hosting strangers in their homes is likely lower for such residents. Two other predictors of peer supply are demand trends and volatility. A city can experience periods of high and low demand

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

due to seasonality, festivals, or sporting events. When the difference in peaks and troughs is large, the provision of accommodations exclusively by dedicated hotel rooms can be inefficiently low. We show that Airbnb's supply share is indeed larger in cities with high demand volatility and, perhaps more intuitively, in cities where demand is trending upward.

We also demonstrate that, over time, peer hosts are more likely than hotels to expand and contract the number of rented rooms in response to price fluctuations. On average, we estimate that supply elasticity is three times higher for peer hosts than for hotels. This difference is consistent with the nature of room supply for hotels and peers. Peer suppliers are highly responsive to market conditions, hosting travelers when prices are high and devoting their accommodations to private use when prices are low. Hotels, meanwhile, have a fixed number of dedicated rooms, meaning that they typically choose to transact even when demand is relatively low and cannot expand capacity during demand peaks.

The heterogeneous entry of peer hosts across cities and over time has implications for their competitive effects on hotels. We estimate reduced-form regressions of hotel performance on Airbnb supply using active Airbnb listings as instruments for available listings, as well as controls for aggregate demand shocks. We find that the negative effect of Airbnb on hotel revenues is concentrated in cities with constrained hotel capacity, where hotels experience a greater reduction in prices than in occupancy rates relative to other cities.

In Section III, we rationalize the stylized facts on peer entry and hotel performance with a model of short-run competition between hotels and peer hosts. In this model, rooms can be provided by dedicated or flexible sellers, and products are differentiated. We define the short-run horizon as one day in one city, during which the capacity of flexible and dedicated sellers is fixed, and aggregate demand is realized. Travelers choose an accommodation option among differentiated hotel and Airbnb rooms. Hotels choose quantities to maximize profits subject to their capacity constraints, while peer hosts act as a competitive fringe taking prices as given.

We use data between 2013 and 2015 from the 10 largest cities, which have also experienced the largest entry of Airbnb, to recover the primitives of our model. Our estimation strategy proceeds in three steps. First, we estimate a random coefficient multinomial logit demand model (Berry, Levinsohn and Pakes (1995)). We augment our estimation with survey data regarding the preferred second choices of Airbnb travelers, which helps us identify substitution between Airbnb and hotel options. Second, we estimate hotels' cost functions assuming Cournot competition between hotels of the same tier. In order to account for the fact that prices steeply increase when occupancy approaches 100%, we follow Ryan (2012) and rationalize these price changes with marginal costs that begin to increase when hotels are close to their capacity constraint. Third, we estimate the cost distribution of peer hosts assuming that they are price takers. Together, these estimates allow us to measure consumer and peer producer surplus, as well as to quantify how surplus would change in the absence of peer supply, or if peer supply were subject to regulations such as lodging taxes or quotas.

Section IV presents our results. We find that consumers' mean utility for Airbnb is lower than for hotels, but that preferences for Airbnb increase between 2013 and 2015. By the end of the sample period, the mean utility from top-quality Airbnb listings is closer to the mean utility of economy and midscale hotels. We find that peer hosts often have higher marginal costs than hotels in the corresponding quality tier and that, consistent with our model, the distribution of peer costs makes peer supply highly elastic.

In the absence of Airbnb, total welfare would be lower and travelers and peer producers would be worse off, while hotels would benefit from less competition. Reporting the effects for 2014, we observe that hotels in the top 10 US cities would increase profits by \$165 million but peer host surplus would go from \$112 million to zero, while consumer surplus would decrease by \$305 million. There are two ways to think about these magnitudes. On one hand, since peer production in the baseline scenario is responsible for just 3% of rooms sold in 2014, the consumer surplus loss is small relative to the revenues in the market. In particular, hotel and peer host revenues in 2014 were a combined \$27.32 billion, meaning that the lost consumer surplus amounts to around 1.1% of total revenues. On the other hand, the benefit to individual consumers and hosts is large. The consumer surplus benefit of Airbnb is \$70 per Airbnb room night and the peer surplus is \$26 per room night.

About half of the consumer surplus comes from Airbnb travelers enjoying new accommodation options and lower prices, while the other half is due to higher prices in the absence of Airbnb. In particular, Airbnb travelers enjoy an additional \$34 per room-night in consumer surplus, which is about 16% of the average room price. Hotel travelers further benefit from lower prices because peer competition reduces the prices they pay by about \$1 per room-night.

Because of the elastic peer supply, actual Airbnb bookings (and thus surplus gains) disproportionately occur when hotel capacity constraints are more likely to be binding, either in busy cities or during major holidays. Indeed, 40% of the consumer surplus loss is concentrated in 19.6% of nights with high demand for accommodations. In the absence of peer supply, travelers in those markets would be unable to easily find a substitute hotel room because hotels are frequently fully booked. We find that a large share of Airbnb bookings, especially during nights with high traveler demand, are market-expanding. In particular, 62% of Airbnb guests would not have switched to a hotel if no Airbnb was available. During periods of high traveler demand, fully 87% of Airbnb customers would not have switched to hotels in the absence of Airbnb.

The concentration of Airbnb bookings in cities and periods of peak demand suggests that, in the absence of Airbnb, hotels would be limited in their ability to increase the number of booked rooms – since they were already operating at or close to full capacity – but would instead be able to increase prices. Indeed, we find that without Airbnb, hotel revenues and profits increase by a higher percentage than hotel rooms sold. In particular, during periods of high demand when hotels cannot increase their available rooms, hotels would be able to increase their revenues by 1.4% and profits by 2.4%.

We also use our model to evaluate two policy proposals affecting peer hosts. During the time period of our sample, cities typically did not collect lodging taxes on peer hosts. However, over time, Airbnb has negotiated agreements to collect lodging taxes on behalf of local jurisdictions. In our first policy counterfactual, we study how the market would be affected if peer hosts faced the same tax rate as hotels in each of our cities. We find that these taxes would reduce the consumer and peer surplus by $95 million (which is 23% of the loss that would have occurred if Airbnb had been completely banned) but would increase lodging tax revenues by $72 million, a 1.8% increase over the baseline scenario. Another policy proposal is to cap the number of days for which peer hosts could accept bookings. We find that a quota limiting Airbnb sales to the 90 days with the largest number of travelers in a city would decrease consumer and peer surplus by $229 million (which is 55% of the loss that would have occurred if Airbnb had been banned).

Finally, Airbnb and its peer hosts have continued growing since 2015 and have become an even larger share of the accommodations market. We use our model to investigate a counterfactual with twice as many Airbnb listings as in 2014. We find that consumer surplus and peer surplus increase by $168 million, which is 39% of the loss that would have occurred if Airbnb did not exist, while hotel profits would decrease by $64 million, or by 1.1% compared to the baseline profit.

In carrying out this study, we contribute to the growing empirical literature on online peer-to-peer platforms (Einav, Farronato and Levin (2016)). Relatively few papers have looked at the effect of online platforms on incumbents, among which Zervas, Proserpio and Byers (2017) for Airbnb, Kroft and Pope (2014) and Seamans and Zhu (2014) for Craigslist, and Aguiar and Waldfogel (2018) for Spotify. While we do estimate the effects on incumbent firms, we also examine the effect on consumers and new producers. In addition, we highlight important dimensions of heterogeneity in the effect of Airbnb across cities and over time. A complementary paper to ours is that by Cohen et al. (2019), who use discontinuities in Uber's surge pricing policy to estimate the consumer surplus from ride-sharing. While both we and Cohen et al. (2019) find that successful peer-to-peer platforms generate substantial consumer surplus, these scholars ignore the impact of ride-sharing on incumbent taxi operators. In particular, their estimation of consumer welfare from ride-sharing rests on the assumption that incumbents do not change their behavior. In contrast, we incorporate capacity constraints and allow for hotel prices to adjust in the absence of Airbnb. This is important for our setting because even travelers who book hotel rooms benefit from Airbnb through lower prices. Like Cohen et al. (2019), Castillo (2020) quantifies the benefits of surge pricing from Uber while Lam and Liu (2019) extend the focus to estimate a model of competition between Uber, Lyft, and taxis using data from New York. Finally, Almagro and Dominguez-Iino (2020) and Calder-Wang (2021) estimate the externalities that Airbnb has on neighborhood amenities and the rental market, respectively, both of which affect where local residents choose to live.

Another related stream of research studies the role of peer-to-peer markets in enabling rental markets for durable goods. Filippas, Horton and Zeckhauser (2020) derive a theoretical equilibrium model for the ownership and rental of durable goods, and make predictions on the existence and size of rental markets across different product categories. Fraiberger and Sundararajan (2019) calibrate a model of car usage and quantify the expected reduction in car ownership as a result of peer-to-peer rental markets.

Other work on peer-to-peer markets has focused on the market design aspects of reputation systems (Bolton, Greiner and Ockenfels (2012), Fradkin, Grewal and Holtz (2019), Nosko and Tadelis (2019)), search (Horton (2014), Fradkin (2019)), and pricing (Einav et al. (2018), Hall, Kendrick and Nosko (2019)). Though these are important market design decisions affecting the welfare that Airbnb generates for peer hosts and travelers, we do not model them in this paper, instead taking them as given. Complementary work by Lewis and Zervas (2021) finds sizable benefits for hotel travelers from online reviews, which are a feature of both Airbnb and hotels throughout our sample.

We document that host supply is highly elastic on the margin. This is consistent with analyses of suppliers on Taskrabbit (Cullen and Farronato (2021)) and Uber (Chen (2016), Hall, Kendrick and Nosko (2019)).[2] Finally, in our analysis of growth heterogeneity across cities, we contribute to the literature on technology adoption and diffusion (e.g. Griliches (1957) and Bass (1969)).

The paper is structured as follows. In the next section, we present the data and document geographic and temporal heterogeneity in the size of Airbnb, comparing the short-run elasticities of Airbnb and hotel supply, and estimating average competitive effects of Airbnb on hotel prices and occupancy rates. Section III introduces a short-run model of demand and differentiated supply of accommodations. We also discuss our empirical strategy for structurally estimating the parameters of our model that determine consumer utility and supplier costs. We provide our estimation results and counterfactual scenarios in Section IV, and conclude in Section V.

II. Data and Stylized Facts

In this section, we describe our data on Airbnb and hotels, and document some stylized facts on the entry of Airbnb and its effects on hotels, which motivate our structural model in the next section.

[2] However, unlike Airbnb, platforms that leverage people's time rather than a spare room, like Uber, have to contend with labor market regulations related to worker benefits and the classification of service providers as contractors or employees.

We first explain why we take Airbnb as representative of peer entry into the accommodation market. Airbnb describes itself as a trusted community marketplace for people to list, discover, and book unique accommodations around the world — online or from a smartphone. The marketplace was founded in 2008 and has more than doubled in total transaction volume for every subsequent year until at least 2015, the end of our sample period. The company has created a market for a previously rare transaction: the short-term rental of rooms to strangers. In the past, these transactions were not commonly handled by single individuals because there were large costs to finding a match, securely exchanging money, and ensuring safety.

Airbnb plays a variety of fundamental roles in enabling peer transactions. These include marketing the platform, developing the search interface and algorithms, hosting and curating online reviews, processing payments, and providing customer service. We treat these as a black box throughout the paper, meaning that we cannot separate the share of consumer utility generated by the platform relative to the share of utility generated by peer hosts. The role of Airbnb in pricing warrants special attention. Airbnb has a split fee structure with a 3% fee to the host and a variable fee to the guest. Fee rates tend to decrease relative to the total value of a booking, but they are not otherwise chosen strategically in response to specific demand or supply conditions. Airbnb has also implemented automated pricing for hosts, but this occurred primarily after our main estimation sample period.[3]

We use Airbnb data to study the welfare effects of facilitating peer entry in the accommodation market. While Airbnb is not the only company serving this market, it is the dominant platform in most US cities. Indeed, the most prominent competitor is Homeaway/VRBO, a subsidiary of Expedia, which has historically focused on rentals of entire homes in vacation destinations, such as beach and skiing resorts.[4] Starting in Q4 of 2019, we have data on gross booking value from mandatory SEC filings by both companies (Airbnb (2020) and Expedia (2019)). Airbnb's gross booking value in Q4 of 2019 ($8.6 billion) was almost four times greater than that of Homeaway/VRBO ($2.3 billion).

Our proprietary Airbnb data consist of information aggregated into four groups based on the type of listing, ranging from luxury to economy. The variables we observe for each listing type include the number of bookings, active and available listings, as well as average transacted prices. An available listing is defined as one that is either booked through Airbnb or is open to being booked on the date of stay according to a host's calendar. The problem with this definition is that hosts generally update their calendars in response to room demand, blocking off dates as unavailable only after receiving a request to book. Thus, fewer listings tend to be shown as available during high-demand periods than in periods of low demand

[3]Airbnb added an automated pricing option ('Smart Pricing') in November 2015 (https://www.cnbc.com/2015/11/12/airbnb-launches-smart-pricing-for-hosts.html) and price suggestions ('Price Tips') in June 2015.

[4], accessed in May 2020.

(see Fradkin (2019) for evidence). To adjust for the problem of demand-induced calendar updating, we expand the Airbnb definition of *available listings* to include rooms that were sent an inquiry for a given stay and later became unavailable for the corresponding dates (see Online Appendix A for more details). In the rest of the paper, the term *available listings* refers to this adjusted measure. An *active listing* is defined as a listing that is available to be booked or that has at least one upcoming booking. Average transacted prices are calculated across all booked rooms on a given date, regardless of the time of booking.

We categorize Airbnb listings into four types: *Airbnb Luxury*, *Airbnb Upscale*, *Airbnb Midscale*, and *Airbnb Economy*.[5] We define listing types using the following algorithm. On the Airbnb servers, we first run a city-level hedonic regression of the transacted nightly price on listing fixed effects, date fixed effects, and bins for the number of five-star reviews and trip duration.[6] This regression is run at the level of a listing-day pair, conditional on the listing being booked for that particular day. Second, we extract the listing fixed effects and use Bayesian shrinkage to shrink fixed effects towards the mean. Third, we compute quartiles of listing quality and categorize a listing in a given quartile if the sum of the shrunken listing fixed effect and the corresponding review count fixed effect falls into the appropriate range. For each city and day, we aggregate price and quantity information at the level of these four listing quartiles before pulling the data from the Airbnb servers for use in our study. This procedure allows us to account for heterogeneity in Airbnb listing types without specifically modeling detailed geographic and room type characteristics at a city level.[7]

The hotel data come from Smith Travel Research (STR), an accommodation industry data provider that tracks over 161,000 hotels. Our sample contains daily prices, rooms sold, and rooms available in the 50 largest US cities for the period between January 2011 and December 2015.[8] STR obtains its information by running a periodic survey of hotels, which collects data on the daily revenue attributable to hotel room bookings, total rooms booked, and total rooms available. For the 50 largest markets, 68% of properties have been surveyed, covering 81% of available rooms. STR uses supplementary data on similar hotels to impute outcomes for the remaining hotels that are in their census but do not participate in the survey. The data are then aggregated using a six-tier scale from luxury to economy, based on the quality and amenities of the hotels. These data can therefore tell us, for example, the average transacted price, number of rooms available, and number of rooms sold on January 10^{th}, 2013 for midscale hotels in

[5]These categories are defined solely for the purpose of this paper and do not correspond to any metric used by Airbnb itself. As part of our agreement with Airbnb for this project, we cannot use listing-level data. However, we were able to classify individual listings into these four groups at our own discretion.

[6]The bins for the number of five-star reviews are: 0, 1, 2-3, 4-5, 6-10, 11-25, 26-50, 51-100, ≥ 101. The bins for nights are 1, 2, 3, 4 - 5, 6 - 7, 8 - 14.

[7]We consider the role of location within a city in Online Appendix D.

[8]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.

San Francisco.

A. Descriptives

We first use our data to describe Airbnb's growth. Airbnb room supply has grown quickly in the aggregate, but its growth has been highly heterogeneous across geographies. Figure 1 plots Airbnb room supply as a share of total rooms (available Airbnb listings divided by the sum of Airbnb listings and hotel room capacity).[9] Even among the top 10 cities in terms of listings, there are high-growth markets like San Francisco and New York, as well as slow-growth markets like Chicago and DC. This growth is specific to the peer-to-peer sector and does not reflect broader growth in the supply of short-term accommodations (see Online Appendix Figure E1).

Temporal heterogeneity exists within cities in the Airbnb share of room supply. These fluctuations are especially prominent in New York: Figure 1 shows large spikes in the number of available Airbnb listings during New Year's Eve, while similar peaks are visible in Austin during the South by Southwest festival. The figure suggests that market conditions during these spikes are especially conducive to peer-to-peer transactions.

Table 1 shows city-level descriptive statistics relating to hotels and Airbnb. Each observation is a city. For every city, we compute the average transacted price per room-night between January 2011 and December 2015. The table displays the mean and standard deviation of these average daily prices across the 50 cities in our sample, as well as other metrics computed in an analogous manner. In the average city, hotels charge \$111 per room-night and their occupancy rate, defined as the share of available rooms that are booked, is 67%. Perhaps surprisingly, Airbnb has very similar transacted prices (\$114) and much lower occupancy rates (16%).[10] The within-city standard deviation of these outcomes varies greatly across cities. For example, the city at the 25th percentile has a standard deviation of hotel prices of \$10 (\$23 for Airbnb prices), while the city at the 75th percentile has a standard deviation of \$23 (\$39 for Airbnb prices). This indicates that cities do not only differ in terms of prices and occupancy rates – though these are consistently higher in some cities – but also in the extent to which market conditions fluctuate over time.

During our sample period, Airbnb comprises a small share of available rooms, at an average of 4% in the last quarter of 2015 and falling between 1% and 6% (25th and 75th percentiles) in most cities. Since Airbnb listings are typically able to host more guests, we can we control for differential guest occupancy of hotel rooms and Airbnb listings (we leave the details to Section III.A). We find that across all cities Airbnb listings can host 5% of potential guests. Finally, Airbnb

[9] Airbnb uses the terms "available listings" and "active listings" in financial filings to reference metrics that do not exactly coincide with ours (Airbnb (2020)).

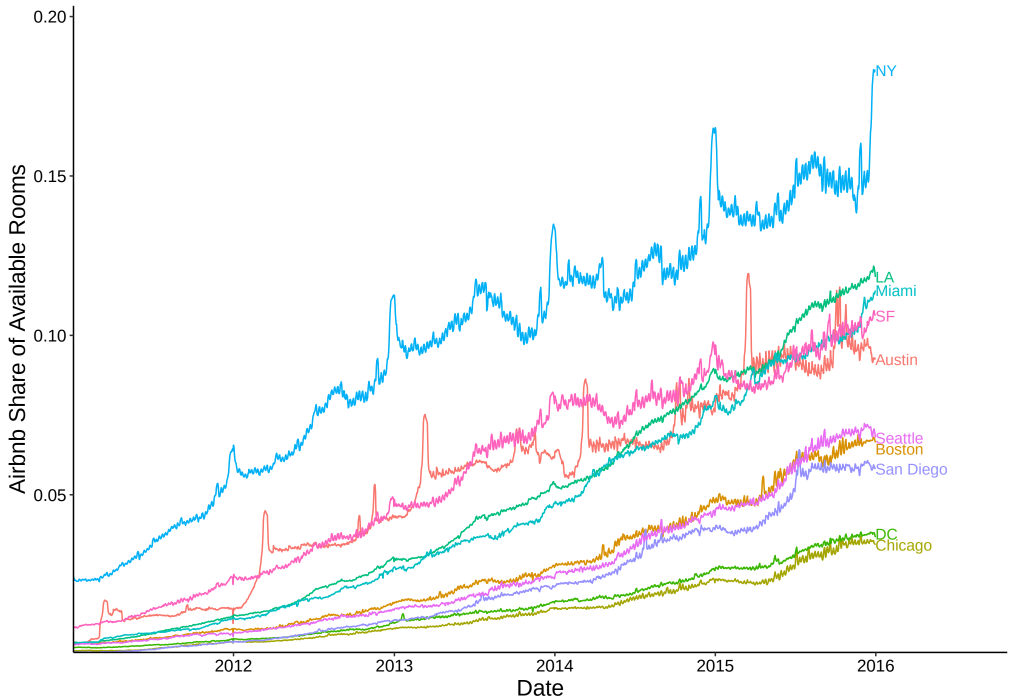
[10] Recall that our definition of available listings underestimates occupancy by construction, since its denominator includes rooms that turn out to be unavailable.

Table 1—: Descriptive Statistics

Statistic	N	Mean	St. Dev.	25 Pct	Median	75 Pct
Mean Hotel Occupancy	50	0.67	0.07	0.62	0.66	0.72
Std Dev Hotel Occupancy	50	0.14	0.03	0.12	0.14	0.15
Mean Hotel Price in $	50	110.77	35.66	88.45	100.90	124.29
Std Dev Hotel Price	50	17.97	9.84	10.42	14.98	23.22
Mean Hotel Revenue ($ ’000s)	50	3,945	3,697	1,639	2,630	5,013
Mean Airbnb Occupancy	50	0.16	0.05	0.13	0.14	0.20
Std Dev Airbnb Occupancy	50	0.10	0.02	0.08	0.10	0.11
Mean Airbnb Price in $	50	113.93	25.80	97.76	103.77	125.78
Std Dev Airbnb Price	50	32.09	12.43	23.18	29.41	38.66
Mean Airbnb to Hotel Price Ratio	50	1.08	0.28	0.94	1.03	1.16
Std Dev Price Ratio	50	0.32	0.16	0.21	0.29	0.37
Airbnb Share of Available Rooms	50	0.04	0.03	0.01	0.02	0.06
Airbnb Share of Potential Guests	50	0.05	0.04	0.01	0.03	0.08
Airbnb Share of Housing Units	50	0.001	0.001	0.0004	0.001	0.002

Note: 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 metrics for hotels and Airbnb listings between January 2011 and December 2015. The metrics we consider are occupancy rates, prices per room-night, revenues, ratio of Airbnb to hotel prices. The last three rows show Airbnb size as a share of available rooms, potential guests, and housing units in the last quarter of our sample, October - December 2015. The Airbnb share of available rooms is computed as the average daily share of available rooms (Airbnb listings divided by the sum of Airbnb listings and hotel rooms). The Airbnb share of potential guests is computed as the average share of available rooms adjusted for their realized capacity, i.e. number of guests occupying a room. To make this adjustment, we have data on Airbnb realized number of guests per room at the city-day-listing type level. Since we do not have the same metric for hotels, we assume that the typical hotel has the same number of average guests as a *Midscale* Airbnb listing in the same city. The Airbnb share of potential guests is typically higher than the Airbnb share of available rooms because an Airbnb listing is on average occupied by more guests than hotel rooms. Finally, the Airbnb share of housing units is the average of the ratio of available Airbnb listings divided by the number of housing units in the Metropolitan Statistical Area.

Figure 1. : Growth of Airbnb



Note: The figure plots the size of Airbnb over time in 10 selected cities. The y-axis is the share of Airbnb listings out of all Airbnb listings and hotel room capacity on a given day. The 10 selected cities are those with the largest number of listings on Airbnb at the end of our sample period among the 50 US major cities. Online Appendix Figure E1 shows that hotel room capacity has been fairly stable over the same time period.

listings represent less than 1% of total housing units for all cities in our sample.

The rest of this section highlights three important stylized facts about peer entry. First, differences in peer entry across cities can be predicted by proxies for hotels' costs of expanding room capacity, population demographics that may affect peers' costs of hosting strangers, and proxies for growth and variability in the total number of travelers. Second, peer supply is very responsive to price, quickly expanding and contracting in response to changes in demand. In fact, peer supply is three times as elastic as hotel supply, which is capped at the maximum number of hotel rooms built in a given city. Finally, peer supply exerts competitive pressure on hotels, negatively affecting their revenues. However, this impact is largely limited to hotel prices rather than occupancy rates, especially in cities where hotels are capacity-constrained. In Sections III and IV we focus on the cities that experienced the largest entry of Airbnb, and thus the largest effects, to quantify the welfare benefits of peer entry.

B. Predictors of Peer Entry Across Cities

In this section, we focus on differences in the size of Airbnb across the 50 cities in our sample and show that predictors of Airbnb size include proxies for costs and demand characteristics in the accommodation industry. Awareness of the Airbnb platform grew between 2011 and 2015, leading to a continuous increase in the number of hosts joining the platform (Figure 1). We assume that the last quarter in 2015, the end of our sample period, provides a valid proxy for the long-run heterogeneity in Airbnb penetration across cities. In particular, if Airbnb represented a larger share of available rooms in New York than Boston in 2015, we assume that, in equilibrium, Airbnb will still be larger in New York than in Boston. We therefore base our analyses in this section on the average Airbnb share of available rooms in October-December 2015.[11]

Figure 2 shows the correlation between Airbnb's share of available rooms in 2015 and daily revenues per available hotel room in 2011, the beginning of our sample period. Not surprisingly, the size of Airbnb is positively correlated with the average revenue per available hotel room in a city, with the highest values of hotel revenues and the penetration of peer hosts both found in New York.

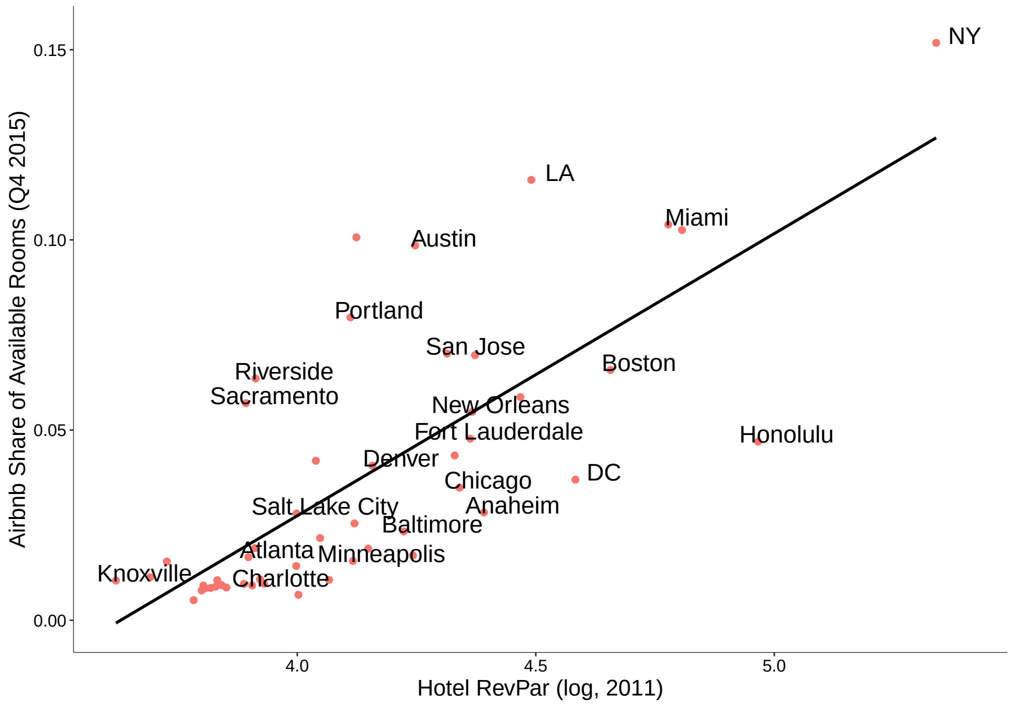
One reason for high revenue per available hotel room is the difficulty of expanding hotel room capacity, since there are high fixed costs to building and expanding hotel facilities. As such, we should expect more peer entry in cities with high fixed costs for hotels. A second reason for high revenue per available hotel room has to do with demand trends and fluctuations. First, since hotels must pre-commit to capacity and any adjustments in the form of new hotel buildings take 3 to 5 years to complete, unforeseen growth in demand will create an inefficiently low hotel supply. Peer hosts, on the other hand, can use their spare rooms to host travelers, so they can respond much more quickly than hotels to growth in demand for accommodations. Second, even if overall demand does not trend upward over time, there can be large fluctuations during high and low travel seasons. It is typically inefficient for hotels to have enough dedicated capacity to absorb all potential travelers in times of peak demand, because doing so would lead to many unoccupied rooms most of the year. In contrast, flexible sellers are able to provide additional supply during peak times, when their rooms are especially valuable to travelers. This implies that we should expect higher demand growth and higher demand variability to both be predictive of the entry of peer suppliers.

In addition to factors influencing the price that hosts can expect to receive for letting strangers stay in their home, the monetary and non-monetary costs of hosting also play an important role. Although many factors affect the costs of hosting, we focus on those related to demographics.[12] For example, an unmarried

[11] Using other averages of the Airbnb share of available rooms, (e.g., December 2015, all of 2015, or any other year in the sample period), leads to similar patterns in Airbnb's size across cities.

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

Figure 2. : Airbnb Penetration and Hotel Revenues per Available Room



Note: This figure plots the size of Airbnb against hotels' average revenue per available room for each of the 50 cities in our sample. The size of Airbnb is measured as the average daily share of Airbnb listings out of all hotel rooms and Airbnb listings available for short-term accommodation. The average is computed over the last quarter of 2015. The hotels' revenue per available room is the daily ratio of total hotel revenues divided by the number of available hotel rooms, averaged over the course of 2011. The fitted line weighs each city equally.

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, during which time their residence is vacant and can be rented on Airbnb.

How do we measure hotel fixed costs, demand growth and volatility, and peer hosts' marginal costs? For hotel fixed costs, we use two proxies. The first is the share of undevelopable area, which we take from 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 regulation related to land use in each metropolitan area and is based on a nationwide survey described in Gyourko, Saiz and Summers (2008).[13]

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

We use data on air travelers as a proxy for accommodation demand trends and fluctuations at the city-month level. Though at this point we are simply interested in predicting peer entry, we measure these demand characteristics during the earliest years in our sample in order to reduce the risk of peer entry influencing demand rather than vice versa. 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.[14] With the Sabre data, we compute the growth rate in travelers to a city between 2011 and 2012 and the standard deviation of incoming travelers in 2011. Finally, using data from the Census Bureau, we use the share of unmarried adults and the share of families with children as proxies for the costs of peer hosts at the Metropolitan Statistical Area level.[15]

We use all these predictors in a linear regression of Airbnb penetration:

$$\begin{aligned} share\_airbnb_m = & \alpha_1 saiz_m + \alpha_2 wrluri_m + \\ & \alpha_3 share\_child_m + \alpha_4 share\_unmarried_m + \\ & \alpha_5 airpass\_sd_m + \alpha_6 airpass\_growt_m + \\ & \alpha_7 log(revpar)_m + \alpha_8 log(market\_size)_m + \epsilon, \end{aligned} \tag{1}$$

where m denotes one of the 46 cities for which we have complete data[16] and *share_airbnb* is the Airbnb share of available rooms in the last quarter of 2015. We divide the standard deviation of incoming air travelers by 10,000 to make the coefficient comparable to the other variables. Market size, which was not defined above, is the sum of available hotel rooms and Airbnb listings in the last quarter of 2015. We control for market size in order to isolate the component of the standard deviation of demand that is due to demand variability.

Table 2 displays regression results. Despite the small sample size and the inclusion of potentially redundant proxies for costs and demand, column (1) shows that all factors predict the size of Airbnb in the expected direction, and all coefficients are at least marginally significant. In column (2) we add the average revenue per available hotel room in 2011 as an additional control. The latter variable has a positive and statistically significant coefficient, though including it results in the coefficients of the demand and hotel investment cost proxies decreasing in magnitude and some becoming non-significant. This result suggests that, as expected, demand proxies and hotel investment costs affect peer entry mostly through price and occupancy rates. Taken together, our cost and demand proxies explain between 67% and 76% of the variation in Airbnb size across our

[14] Data from Sabre include the monthly number of passengers by origin and destination airport. We aggregate these observations into a Metropolitan Statistical Area-month measure of air travelers.

[15] Online Appendix Table E1 displays summary statistics for the cost and demand factors that we use as predictors of Airbnb penetration. Online Appendix Figure E2 displays raw correlation plots between each predictor and Airbnb penetration.

[16] We are missing the share of undevelopable area and WRLURI for four of our 50 cities.

cross-section of US cities.

C. Peer Supply Elasticity and Competitive Effects on Hotels

Airbnb bookings fluctuate over time: more rooms are booked during the peak season than in other periods (Online Appendix Figure A1). In this section, we use instrumental variable regressions to document that flexible suppliers are three times as elastic as dedicated suppliers. Combined with the differential entry of Airbnb across cities described in Section II.B, this fact implies that Airbnb impacts hotel performance differently across geographies and over time because peer hosts compete with hotels more in some cities than in others, and do so to a greater degree during certain time periods. Note that this section is only suggestive of the directions of the effects we expect. Section III presents the full structural model and Section IV its results.

To measure the average elasticity of Airbnb supply with respect to price, and compare it to that of hotels, we estimate the following equation:

$$log(Q_{mt}) = \chi log(K_{mt}) + \kappa log(p_{mt}) + \mu_{mt} + \epsilon_{mt}, \tag{2}$$

where Q_{mt} is the number of (hotel or Airbnb) bookings in city m and day t, K denotes capacity – the number of available hotel rooms or Airbnb listings – 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 for hotels and Airbnb. μ_{mt} includes city fixed effects, seasonality (month-year fixed effects), and day of week fixed effects. These fixed effects control for the fact that costs might change by city or over time, for example due to average differences in costs across cities or due to particular periods when hosts are less likely to occupy their residences.

Equation 2 suffers from standard simultaneity bias because the price of accommodations is correlated with demand, and with unobserved fluctuations in marginal costs. Furthermore, in the case of Airbnb, the number of available rooms K_{mt} is itself endogenous because, as shown in the beginning of Section II, hosts may update availability as a function of demand.[17] We discuss each concern in order.

We instrument for price with plausibly exogenous demand fluctuations, which are typically caused by holidays or special events in a city. We use two instruments. The first is the number of arriving (not returning) flight travelers in a city-month, which was introduced in Section II.B. The second comes from Google Trends, which provides a normalized measure of weekly search volume for a given query on Google. Our query of interest is "hotel(s) m," where m is the name of a US city in our sample. We de-trend each city's Google Trends series using a

[17]The same endogeneity issue is not important for hotels because hotel capacity is typically fixed in the short run. Indeed, Online Appendix Figure E1 confirms that the number of hotel rooms has been fairly stable over the course of our sample period, with the exception of New York.

Table 2—: City Characteristics and Size of Airbnb

	Airbnb Share of Rooms (Q4 2015)	
	(1)	(2)
Undevelopable Area	0.036**	0.026*
	(0.017)	(0.015)
Wharton Residential Land Use Index (WRLURI)	0.009*	0.005
	(0.004)	(0.004)
SD. Incoming Air Passengers (2011)	0.002*	0.00003
	(0.001)	(0.001)
% Growth in Air Passengers (2012-2011)	0.125*	0.107*
	(0.067)	(0.058)
% Never Married	0.504***	0.308**
	(0.164)	(0.152)
% Children	−0.399*	−0.218
	(0.203)	(0.182)
Log(Rev. Per Room (2011))		0.061***
		(0.017)
Log(Market Size)	−0.008	−0.012
	(0.008)	(0.007)
Constant	0.052	−0.133
	(0.091)	(0.093)
Observations	46	46
R^2	0.668	0.758

Note: This table shows linear regressions of the size of Airbnb on market characteristics linked to supply constraints, demand volatility, and the costs of hosting (Equation 1). The size of Airbnb is the average daily share of rooms in the last quarter of 2015. 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 Table 1 (for the outcome variable) and Online Appendix Table E1 (for the predictors). Market size is measured as the average number of hotel rooms and Airbnb listings available in the last quarter of 2015. *p<0.1; **p<0.05; ***p<0.01.

common linear trend to remove long-run changes in overall search behavior on Google. We employ the one-week lagged search volume as an instrument, though using other lags or the contemporaneous search volume yields similar estimates. Reverse causality may be a concern here, such that the availability of Airbnb rooms is actually what leads tourists to travel or search for hotels in particular destinations. While we cannot completely rule this out, the relatively small share of Airbnb bookings (under 3% across all cities), at least until the end of our sample period, suggests that this is unlikely.

To control for the fact that room availability on Airbnb is endogenous to demand, we instrument for the number of available listings with the number of active listings, since this metric is less responsive to contemporaneous demand shocks, even though it is highly correlated with the number of listings that are available for rent. We report the first stage regression results in Online Appendix Table E2. For the first stage of hotel supply as well as the first stage of Airbnb supply, we reject the hypotheses of under-identification and weak identification and cannot reject the hypothesis that the joint set of instruments are valid.

Table 3 contains our IV estimates of Equation 2 for Airbnb and hotels separately. Turning first to column (1), a 1% increase in the average hotel daily rate increases hotel bookings by 1.3%. This is about a third as large as Airbnb's elasticity, which is displayed in column (2) and is estimated to be 3.9. Consequently, smaller price fluctuations are needed for Airbnb supply to increase or decrease.[18]

We have shown that the Airbnb supply is three times more responsive to price than that of hotel rooms. The lower elasticity of hotel supply has a simple explanation, which will become clearer in our structural model. To the extent that hotels have a constant marginal cost and a fixed supply, hotel bookings cannot increase in response to increases in demand when demand is sufficiently high. The higher elasticity of flexible supply implies that there are many hosts willing to rent their rooms when prices are high, but prefer not to do so when prices are just a little lower.

Where and when peer hosts decide to enter the market has implications for hotel outcomes, which we focus on next. Since peer hosts are more likely to enter in cities with high hotel revenues, we should expect the competitive effect of Airbnb on hotels to be greatest in these places. To test this, we estimate the effects of peer entry on hotel revenue, occupancy rates, and prices, and how these differ by city.

Before describing our empirical strategy, we discuss the two most important challenges to identifying the effect of Airbnb. Consider the hypothetical scenario where Airbnb supply grows randomly across cities and over time. In this scenario, regressing hotel outcomes on the number of available Airbnb listings would yield

[18]Instrumenting for prices and available Airbnb listings is important. Online Appendix Table E3 presents OLS estimates of Equation 2. As one would expect, the OLS underestimates the elasticity of supply to price and overestimates the elasticity of supply to available listings. The results do not change if we adjust for the fact that Airbnb listings are typically occupied by more guests than the average hotel room, an adjustment we describe in Section III.A.

Table 3—: The Supply Elasticity of Hotels and Peer Hosts

	Log(Hotel Rooms) Boooked + 1)	Log(Airbnb Rooms Booked + 1)
	(1)	(2)
log(Hotel Rooms + 1)	0.543**	
	(0.215)	
log(Hotel Price)	1.289***	
	(0.103)	
log(Airbnb Available Listings + 1)		0.385***
		(0.142)
log(Airbnb Price)		3.893***
		(0.288)
IV	Yes	Yes
City FE	Yes	Yes
Year-Month FE	Yes	Yes
Day of Week FE	Yes	Yes
Observations	90,900	84,959
R^2	0.954	0.774

Note: The table shows results of IV regressions of the log of hotel and Airbnb bookings on the corresponding price and room availability (Equation 2). In column 1 we instrument for hotel prices with the one week lag of the log of the Google Search Trends and the log of arriving (not returning) flight travelers. In column 2 we instrument for both Airbnb prices and the number of available listings. We use three instruments: the one week lag of the log of the Google Search Trends and the log of arriving flight travelers as in column 1, plus the number of Airbnb active listings. First stage results are reported in Online Appendix Table E2 and OLS results are reported in Online Appendix Table E3. Standard errors are clustered at the city level. Adding the city-day observations with no Airbnb bookings (and using hotel prices in column 2) does not change the results. Results would not change if in Column 2 we included the log of departing air travelers and the one-week lag of the log of local Google Search Trends for hotels outside of the city as additional controls. *p<0.1; **p<0.05; ***p<0.01.

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 peaks in size during periods of high demand within each city. Observables like the number of arriving air travelers, city fixed effects, and seasonality fixed effects help us control for this selection, but do not completely solve the endogeneity problem. Thus, we instrument for the currently available Airbnb supply with the number of active listings.

Second, we expect the effects of Airbnb to differ based on whether a city's hotel sector is constrained. We proxy for the elasticity of hotel construction by using the measures of housing supply elasticity constructed in Saiz (2010). Saiz (2010) uses the WRLURI and the share of undevelopable area described in Section II.B to estimate the housing supply elasticity at the city level. Cities with a low supply elasticity are likely to have a more constrained hotel capacity, and, therefore, may see a greater effect of Airbnb.

Our baseline regression specification is:

$$\begin{aligned} y_{mt} =& \alpha_1 \log(airbnb_{mt}) + \alpha_2 \log(airbnb_{mt}) * constrained_m + \\ & \beta_1 \log(hotel\ rooms_{mt}) + \beta_2 \log(hotel\ rooms_{mt}) * constrained_m + \\ & \gamma \log(gtrend_{mt}) + \delta \log(travelers_{mt}) + \theta_{mt} + \nu_{mt}. \end{aligned} \tag{3}$$

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 (instrumented for with the number of active listings), $hotel\ rooms_{mt}$ is the number of available hotel rooms, $gtrend_{mt}$ is the one-week lag of Google searches for hotels in the city, $travelers_{mt}$ is the number of arriving air passengers, and $constrained_m$ is equal to 1 if the housing supply elasticity estimated by Saiz (2010) is below the median value. The vector θ_{mt} includes city fixed effects, quarter-year fixed effects and their interaction with the $constrained_m$ dummy, and day of the week fixed effects and their interaction with $constrained_m$. 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 effects of interest are α_1 and α_2. α_1 is the average short-run elasticity of hotel outcomes to peer supply over our sample period for cities with unconstrained hotel supply. α_2 is the additional effect in cities with constrained hotel supply. The coefficients are identified based on two types of variation. First, there is variation across cities and over time in the number of available listings due to an increasing awareness of Airbnb. Second, there is variation in the availability of listings due to hosts' daily costs of hosting, for which we assume the instrument takes care of removing parts that might be correlated with residual daily demand for accommodations within the city.

Table 4 displays the results of the baseline specification. The coefficient on

Airbnb size in column (1) is close to zero and statistically insignificant, while the coefficient on the interaction term is negative and statistically different from zero at the 5% confidence level. This coefficient implies that a 10% increase in available listings decreases the revenue per hotel room by 0.57%. The coefficient estimates for our demand proxies, Google trends, and arriving air travelers have the correct sign and are statistically significant. The same is true for the coefficient on hotel rooms. Once we break down the effect into a reduction in occupancy rates (column 2) and a reduction in prices (column 3), we see that the negative effect of Airbnb is mostly concentrated on prices in cities with constrained hotel capacity.[19]

Differences in the effect of Airbnb on hotels across constrained and unconstrained cities occur for two reasons. First, for the same level of Airbnb and hotel capacity, the effect of Airbnb is relatively larger on prices if hotel capacity 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 listings constitute a larger share of available rooms. Intuitively, the elasticity of hotel revenues with respect to the size of Airbnb should increase with the Airbnb share of supply, since a 1 percent increase in Airbnb size is a much larger share of the market supply when Airbnb penetration is 3% than when it is 1%. Both conditions are true when analyzing constrained and non-constrained cities separately. Indeed, in December 2015 the average Airbnb supply share in hotel-constrained cities was 5.8%, and only 2.2% in unconstrained cities. At the same time, average hotel occupancy rate was 62.2% in constrained cities and only 55% in unconstrained cities.

Before concluding this section, one caveat is in order. In these specifications, we cannot take advantage of exogenous changes in price that would allow for a valid causal estimate of the effect of Airbnb on hotel performance, something that is possible with a structural model, as discussed in the next section. However, this exercise has helped us to highlight a few facts from the data. We have documented that the entry of peer hosts is higher 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 three times higher than that of dedicated supply. Finally, we have seen that the entry of flexible supply has negative spillovers on the revenue of dedicated suppliers. This negative effect is concentrated in cities with binding hotel capacity constraints and predominantly impacts hotel prices rather than occupancy rates. In the rest of the paper, we focus on the 10 cities that experienced the largest entry of Airbnb, nine of which are in the group of cities with the greatest binding hotel capacity constraints, and consider how the elastic Airbnb supply affects

[19]As before, we present first-stage regression results in Online Appendix Table E4, OLS results in Table E5, and effects by hotel tier in Table E6. The coefficient on Airbnb listings is a statistically significant 0.021 in column (3), which suggests that some spurious correlations may still be present. Online Appendix Table E6 suggests that most of the latter correlation comes from luxury hotels, while the coefficient estimate is smaller and statistically indistinguishable from zero for other hotel tiers.

Table 4—: Hotel Revenues and Airbnb Entry

	Log(RevPAR)	Occupancy Rate	Log(Price)
	(1)	(2)	(3)
log(Incoming Air Passengers)	1.104^{***}	0.371^{***}	0.482^{***}
	(0.063)	(0.041)	(0.040)
log(Google Search Trend)	0.246^{***}	0.076^{***}	0.109^{***}
	(0.042)	(0.012)	(0.024)
log(Hotel Rooms + 1)	-0.936^{***}	-0.521^{***}	-0.089
	(0.326)	(0.137)	(0.168)
log(Hotel Rooms + 1)*	-0.475	0.055	-0.612^{**}
Inelastic Housing Supply	(0.370)	(0.174)	(0.281)
log(Airbnb Available Listings + 1)	0.020	-0.002	0.021^{**}
	(0.016)	(0.007)	(0.010)
log(Airbnb Available Listings + 1)*	-0.057^{**}	-0.002	-0.054^{**}
Inelastic Housing Supply	(0.025)	(0.010)	(0.022)
IV	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes
Observations	90,900	90,900	90,900
R^2	0.740	0.591	0.856

Note: This table shows results of IV estimates of Equation 3, where the size of Airbnb is measured as the number of available listings. The Google search trend is a one-week lag. The instruments for available listings and its interaction with the dummy for inelastic housing supply are the number of active listings and its corresponding interaction with the dummy. The dependent variable is log revenue per available room in column (1), occupancy rate in column (2), and log price in column (3). First stage results are reported in Online Appendix Table E4 and OLS results are reported in Online Appendix Table E5. Results for different hotel tiers are presented in Online Appendix Table E6, and results using different measures of the size of Airbnb are in Online Appendix Table E7. Standard errors are clustered at the city level. *p<0.1; **p<0.05; ***p<0.01.

consumers and hotels over time.[20] This allows us to quantify how hotel capacity constraints and elastic peer supply contribute to the welfare of the agents in the market.

III. Model and Estimation Strategy

In this section, we describe a short-run model that we use to estimate welfare gains from the entry of flexible supply. In our model, hosting services can be provided by dedicated and flexible sellers, who offer differentiated products. The equilibrium consists of daily prices and rooms sold by each accommodation type as a function of the overall demand level and the respective capacities of dedicated and flexible suppliers. We assume hotels are competing against a fringe of flexible sellers. Online Appendix B presents a version of this model with only one hotel type and one type of flexible host, but with more general demand and cost specifications. We prove the existence and uniqueness of the equilibrium under those conditions, as well as comparative statics predictions that are in line with the stylized facts from Section II.

A market n is defined by day t and city m. On the demand side, our model is a random coefficients logit model (Petrin (2002) and Berry, Levinsohn and Pakes (1995)), where rooms are differentiated across hotel tiers and Airbnb listing types. On the supply side, we assume that hotels engage in Cournot competition with differentiated products across tiers. Within a tier, each hotel is undifferentiated. Airbnb hosts are price takers with randomly drawn marginal costs.

Consumer Demand

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

$$u_{ijn} = \mu_{ijn} + \alpha_i(1 + \tau_{jn})p_{jn} + \epsilon_{ijn}. \tag{4}$$

For consumer i, μ_{ijn} represents a mean utility for accommodation j in market n inclusive of preference heterogeneity for the inside options. The price of an accommodation is denoted p_{jn}, while τ_{jn} represents the percent difference between what the travelers pay and what the suppliers receive for accommodation j. For hotels, τ_{jn} is simply the lodging tax rate. For Airbnb rooms, it is a combination of the Airbnb commission fee and the lodging tax rate if Airbnb collects it.[21] Finally, ϵ_{ijn} is an idiosyncratic component with a type I extreme value distribution. We

[20] The 10 cities are Austin, Boston, Los Angeles, Miami, New York, Oakland, Portland, San Francisco, San Jose, and Seattle. Austin is the only city without binding hotel capacity constraints per our definition.

[21] We collect the lodging tax rate from HVS Lodging Tax Reports for hotels (https://www.hvs.com/indepth/ accessed January 2021). For Airbnb, we have the average price paid by travelers, the average price received by hosts, the average tax collected, and the average amount kept by Airbnb as commission for each listing type, city, and night, from which can compute the Airbnb's commission fee and lodging tax rate if applicable.

normalize the value of the outside option to 0 for all markets. This demand specification yields the following quantities for each accommodation type:

$$Q_{jn}(p_{jn}, p_{-jn}) = D_n \int \frac{e^{\mu_{ijn}+\alpha_i(1+\tau_{jn})p_{jn}}}{1+\sum_{j'} e^{\mu_{ij'n}+\alpha_i(1+\tau_{jn})p_{j'n}}} dH(i), \tag{5}$$

where D_n is the market size and H is the joint distribution of consumer heterogeneity. We allow for consumer heterogeneity in how travelers value the inside options (hotels and Airbnb), since this gives the model flexibility in determining what share of Airbnb travelers would substitute towards hotels in the absence of Airbnb. We also allow for consumer heterogeneity in sensitivity to price. We assume that the distribution of consumer heterogeneity is multivariate normal with a mean and variance matrix to be estimated. We do not allow for correlation across distinct components of consumer heterogeneity.

Hotel Supply

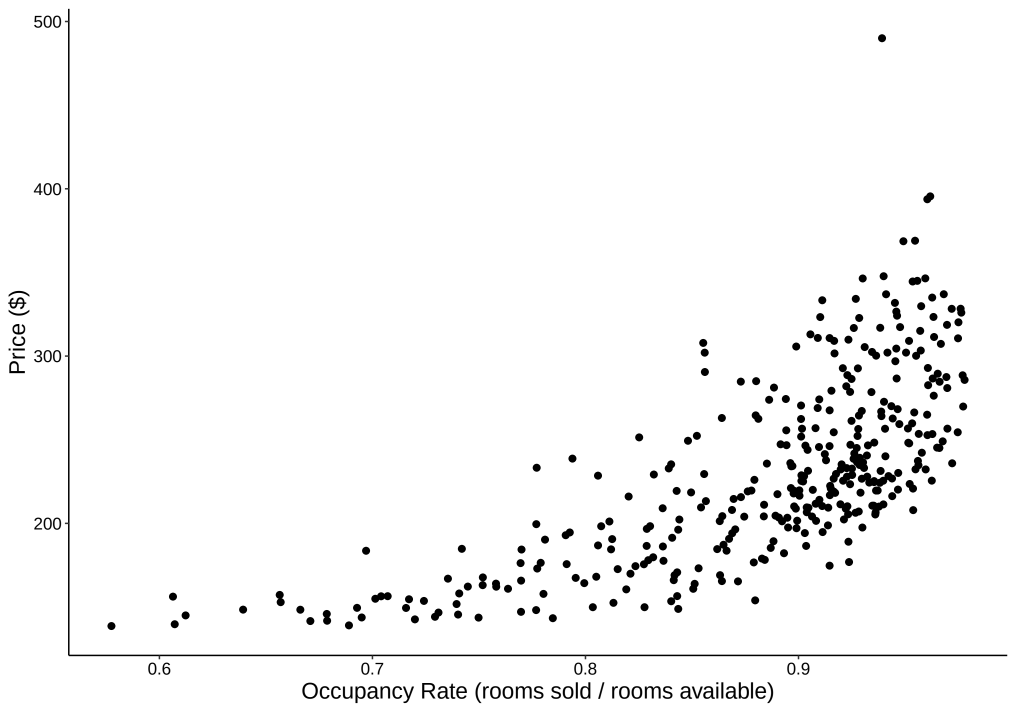
Each hotel competes with other hotels of the same tier, hotels of different tiers, and peer supply. We assume that this competition takes the form of a Cournot equilibrium. Hotels of tier h, where $h \in$ {*luxury, upper-upscale, upscale, upper-midscale, midscale, economy*}, have aggregate room capacity K_{hn}. Since there are multiple hotels within each tier, we need to distinguish between tier-level and hotel-level quantities. We let Q_{hn} denote the tier-level number of rooms sold. We assume no differentiation in room quality within a tier, so the number of rooms sold by each hotel, denoted q_{hn}, is the ratio of aggregate quantity divided by the number of hotels. Analogously, tier-level capacity is denoted K_{hn}, while hotel-level capacity is k_{hn}.[22]

We must also match the fact that prices increase sharply as the number of rooms sold approaches the number of available rooms. Although occupancy rates never reach 100% at the tier level in practice, prices start increasing before then (Figure 3). This is because, although we model hotels as homogeneous within each tier, some individual hotels may sell out before others and this may result in sharply increasing tier-level prices. In addition, if hotels face uncertainty about the actual level of demand when setting prices, increases in expected demand will increase the probability of hitting capacity constraints, thus increasing prices before realized demand reaches 100%. We allow our model to fit this increasing price profile by estimating an increasing cost function for hotels that kicks in as soon as hotel occupancy is at least 85% within a tier. The estimation of increasing marginal costs as production approaches capacity constraints was previously used by Ryan (2012) to estimate the cost structure of the cement industry.[23]

[22]STR provides us with the number of hotels in a given tier, day, and city.

[23]We do not model individual hotels' capacity constraints and stock-outs as in Conlon and Mortimer (2013) and Lewis and Zervas (2021), because we do not have data from individual hotels and because doing so would significantly complicate estimations of demand and supply. Our simplifying

Figure 3. : Prices and Occupancy Rates



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

For these reasons, we assume that hotels' variable costs are comprised of two parts: a constant marginal cost c_{hn}, and an increasing marginal cost $\gamma_{hn}(q_{hn} - \nu k_{hn})$, which starts binding as quantity approaches the capacity constraint. Given the above discussion, we set $\nu = 0.85$. So, instead of solving a maximization problem subject to a capacity constraint, each hotel selects its quantity to maximize the following profit function:

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

We assume that hotels observe all components of demand and competitors' costs, so that there is no uncertainty about whether $q_{hn} > \nu k_{hn}$ or not. Letting N_{hn} denote the number of hotels within tier h, we have $q_{hn} = \frac{Q_{hn}}{N_{hn}}$. Taking advantage of the implicit function theorem, the optimization problem gives rise

choice understates the strategic effect of Airbnb, especially during periods of peak traveler demand, because incorporating hotel capacity constraints would increase the curvature of the supply function and decrease consumer choice as hotels reach capacity. We also estimated the supply with thresholds of 80% and 90% and found that these did not make much of a difference for our counterfactuals.

to the following first order condition:[24]

$$p_{hn} = -\frac{1}{N_{hn}}\frac{Q_{hn}}{Q'_{hn}} + c_{hn} + \gamma_{hn}\mathbb{1}(q_{hn} > \nu k_{hn})(q_{hn} - \nu k_{hn}), \tag{6}$$

where Q_{hn} is tier-level room demand from Equation 5, and Q'_{hn} is the derivative with respect to its own price.

Peer Supply

Peers of each quality type a, where $a \in \{$*Airbnb luxury, Airbnb upscale, Airbnb midscale, Airbnb economy*$\}$, with total available listings K_{an}, take prices as given. Hosts draw marginal costs from a normal distribution with mean ω_{an} and standard deviation 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:

$$Q_{an}(p_{an}, p_{-an}, p_{hn}) = K_{an}Pr(c \leq p_{an}) = K_{an}\Phi\left(\frac{p_{an} - \omega_{an}}{\sigma_{an}}\right). \tag{7}$$

Equilibrium

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

A. *Estimation Strategy*

We estimate demand, hotel supply, and peer supply separately.

Starting with demand, the high-level choices are the market size, the moments to match, and the instruments used. However, we first need to make a normalization. Since Airbnb listings can, on average, host more guests than hotel rooms, we adjust quantities so that the occupancy is comparable across Airbnb listings and hotel rooms. To do this, we take advantage of the fact that we have information on the average number of guests for Airbnb bookings. In addition, lower-quality Airbnb listings are typically private rooms with smaller capacity than standard hotel rooms. For this reason, we assume that each hotel room is occupied by as many people as the average number of occupants of Airbnb Midscale listings in the same city. Given this adjustment, our quantities, prices, and estimates should be interpreted as referring to room-nights with standard hotel occupancy.

We use data from the 10 largest cities in terms of the share of Airbnb bookings

[24] The objective function is not differentiable at $q_{hn} = \nu k_{hn}$, but otherwise the first order condition holds everywhere else.

in our sample.[25] Our estimation sample starts in 2013 and continues until July 1, 2015. We restrict the sample in this way for three practical reasons. First, in other cities and time periods, the estimation is complicated because the Airbnb market shares are often close to zero. Second, the reduced form results in Section II suggest that the effects of Airbnb in those markets will be limited when the Airbnb market share is close to 0. For the same reason, we also drop Airbnb options if their share of available rooms is less than 0.5% on a given day and city. Finally, we exclude the second half of 2015 and use it to validate our estimates out of sample.

One key choice we must make in the estimation is D_n, the total number of consumers looking to book accommodations. The choice of D_n will affect market shares for hotels and Airbnb, as well as the share of potential travelers choosing to stay home, travel to other locations, or stay in alternative accommodations, e.g. with friends and family. We set D_n equal to two times the average number of rooms booked in the corresponding month in each city in 2012.[26] This assumption permits the potential number of travelers to vary seasonally across cities, and it allows for both hotel substitution, as hotel travelers switch to Airbnb, and market expansion, as travelers switch from the outside option to Airbnb. We rationalize any remaining variation over time in the total number of travelers booking accommodations with mean utilities for inside options that vary as a function of unobservable and observable characteristics.

The second choice is the set of moments that we match to the data. We construct two types of moments for the demand estimation: the standard BLP moments (market share moments) and a moment disciplining the estimated model to match survey data on the hypothetical choice of Airbnb users if Airbnb did not exist (substitution moment).

Our market share moments are

$$m_{1jn} = \left[\delta_{jn} - \hat{\delta}_{jn}\right] Z_{jn}, \tag{8}$$

where δ_{jn} is the realized mean utility from accommodation j in market n that rationalizes the observed market shares, and $\hat{\delta}_{jn}$ is the mean utility predicted from the vector of parameters to be estimated. $\hat{\delta}_{jn}$ is the component of utility from Equation 4 that does not differ across individual travelers, and is a function of observable and unobservable characteristics of the different types of accommodations. In addition to prices, utility is a function of day of week fixed effects; city-tier-month fixed effects to account for different preferences across quality tiers, locations, and seasons; city-specific and Airbnb-city-specific linear time trends; and the log of 1-week lagged Google searches for hotels in the city.

[25]The 10 cities are Austin, Boston, Los Angeles, Miami, New York, Oakland, Portland, San Francisco, San Jose, and Seattle.

[26]The total market size is not identified when estimating demand, so we follow the convention of setting market size to a plausible value. Small changes in the multiplier relative to 2 do not substantially affect estimated price elasticities or our counterfactual analysis.

The vector Z_{jn} includes all determinants of utility described above except for prices. Given price endogeneity and consumer preference heterogeneity, we exploit supply-side variation that affects prices and substitution across options. Our first instrument takes advantage of the fact that hotel capacity constraints affect prices when they are binding but are uncorrelated with daily demand shocks. In particular, a change in demand when capacity constraints are binding will have a much greater effect on prices than when they are not binding. We proxy for this effect by using the ratio of the log of Google searches for hotels and the available hotel rooms. Our next instrument is the lodging tax rate, which may be different for hotels and Airbnb options. The lodging tax rate varies due to changes in the rate by local authorities as well as Airbnb starting to collect lodging taxes on behalf of certain jurisdictions. Finally, as in our reduced form, we use variation in hotel and Airbnb capacity. We use the number of hotel rooms and the number of active Airbnb listings, and we interact them with tier fixed effects.

The substitution moment comes from survey data on alternative accommodation choices of travelers booking on Airbnb. Airbnb conducted surveys of guests in four of the sampled cities during 2013 and 2014, asking the following question: "If Airbnb had not been available, what would you have done?" Between 19% and 42% of guests across cities said that they would not have booked a hotel, effectively choosing the outside option. A simple average across cities yields a share of 32% of respondents who would choose the outside option, which we use in our estimation.[27]

We match the survey responses in our model by computing the share of Airbnb travelers who would have booked a hotel at the observed prices had Airbnb not been available. To predict the share of Airbnb travelers choosing hotels in the absence of Airbnb, we first note that the share of travelers choosing the outside option in market n is $s_{on} = \int \frac{1}{1+\sum_{j'} e^{\mu_{ij'n}+\alpha_i(1+\tau_{jn})p_{j'n}}} dH(i)$. Airbnb's market share, denoted $s_{airbnb,n}$, is equal to the sum of the market shares of each Airbnb option available in market n. If Airbnb listings were not available, the market share of the outside option would be $s_{on^*} = \int \frac{1}{1+\sum_{j'\in \text{hotel}} e^{\mu_{ij'n}+\alpha_i(1+\tau_{jn})p_{j'n}}} dH(i)$. Therefore, in a specific market n we compare the ratio $\frac{s_{on^*}-s_{on}}{s_{airbnb,n}}$ with 32%, the survey's share of Airbnb travelers choosing the outside option:

$$m_{2n} = \left(100\frac{s_{on^*} - s_{on}}{s_{airbnb,n}} - 32\right).$$

[27]In 2015, Morgan Stanley and AlphaWise conducted a representative survey of 4,116 adults in the US, UK, France, and Germany. In the survey, they asked respondents about their travel patterns. 12% of respondents had used Airbnb within the past year and when asked which travel alternative Airbnb replaced, 58% of respondents answered something other than a hotel (See Nowak et al. (2015)). We believe that the major reason for the differences between the Airbnb and Morgan Stanley surveys is that the latter sampled guests at various types of destinations, including resorts and European cities. There are typically more non-Airbnb and non-hotel options for guests in these locations.

When we sum the substitution moments across markets, we weigh each market with the same set of available Airbnb options equally. For example, markets where only *Airbnb Luxury* options are available receive a weight equal to the share of Airbnb rooms sold in those markets out of all Airbnb rooms sold ($\frac{\sum_{n' \text{ with Airbnb luxury only}} s_{airbnb,n'} D_{n'}}{\sum_n s_{airbnb,n*} D_n}$). This results in the highest weight being placed on markets where all Airbnb options are available, which is most frequently the case. In the data, we have 15 possible combinations of Airbnb options available. This gives us the following aggregate moment:

(9)
$$m_2 = \frac{1}{N} \sum_{i=1}^{15} \left[\frac{\sum_{n' \text{ has Airbnb options in group i}} s_{airbnb,n'} D_{n'}}{\sum_n s_{airbnb,n} D_n} \sum_{n' \text{ has Airbnb options in group i}} m_{2n'} \right].$$

where N is equal to 9,110, the number of markets.

It is useful to provide an intuition for how the variation in the data allows us to estimate the demand parameters. Our descriptive statistics show that the prices of hotels and Airbnb options, unadjusted for different number of occupants, are similar. This fact, together with the relatively high substitution rate between hotels and Airbnb rooms derived from survey responses, suggests that the mean utilities of hotels and Airbnb options should be fairly similar. In practice, however, we also observe very different market shares, with hotels much more popular than Airbnb. The market share and substitution moments help us rationalize these two patterns in the data. On the one hand, the substitution moment helps us identify consumer preference heterogeneity (the random coefficients on price and the inside option). On the other, differences in market shares rationalize mean utilities that will be higher for hotels than for Airbnb options. We discuss computational details and the sensitivity of our estimates to our identifying assumptions in more detail in Online Appendix C.

Once we obtain demand estimates that let us compute Q_{hn} and its price derivative, we estimate the supply function from Equation 6 using a linear IV approach:

$$p_{hn} + \frac{1}{N_{hn}} \frac{Q_{hn}}{Q'_{hn}} = \theta X_{hn} + \gamma_{hn} \mathbb{1}(q_{hn} > \nu k_{hn})(q_{hn} - \nu k_{hn}) + \epsilon_{hn}. \tag{10}$$

X_{hn} includes city-tier fixed effects, city-day of the week fixed effects, year-month fixed effects, and city-specific linear time trends. We allow for γ_{hn} to vary by city and by tier separately. We instrument for the increasing cost component using interactions of the lagged Google search trend with city fixed effects and hotel fixed effects. These instruments proxy for demand shocks that affect the likelihood that capacity constraints bind, and as a result are both relevant and exogenous in the supply equation. The supply equation is then estimated jointly using all markets.

Finally, the supply of Airbnb can be estimated separately using another linear

IV regression for the same sample period. Equation 7 implies that $\Phi^{-1}\left(\frac{Q_{an}}{K_{an}}\right) = \frac{\omega_{an}}{\sigma_{an}} + \frac{1}{\sigma_{an} p_{an}}$, where the left-hand side is the inverse of a standard normal cumulative distribution function calculated at a value equal to the share of booked rooms out of all Airbnb active listings. We estimate 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 of type a, p_{an} is the average transacted price of Airbnb type a in market n, and, as in the case of the hotel supply regression, X_{an}, it includes city-tier fixed effects, city-day of the week fixed effects, year-month fixed effects, and city-specific linear time trends. We instrument for the transacted price with the log of Google search trends and the log of incoming air passengers.

After estimating the above equation, we can transform the coefficients into the following peer cost parameters:

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

IV. Results

In this section, we discuss the results of our estimation. We first review our estimated parameters.[28] Then, we discuss the effects of Airbnb and government regulation on consumer surplus, hotels' and hosts' bookings, revenues, and surplus, and on lodging taxes.

A. *Parameter Estimates*

Table 5 displays the estimates of demand parameters that are common across cities and accommodation options. We first discuss the parameters governing the distribution of price sensitivity across travelers. The mean price coefficient is -.031 and the standard deviation is .004. The standard deviation is imprecisely estimated, but our estimates are consistent with existing work on hotel demand (Koulayev (2014)). Google search trends are estimated to have a positive effect on demand. We also estimate some level of heterogeneity in preferences for booking the inside option (a hotel or Airbnb room), although the coefficient is not significant at the 5% confidence level. Comparing the first and the second columns in the table, there is little difference between the utility parameter estimates between the demand model with consumer preference heterogeneity and the standard logit model.

Figure 4 displays the mean willingness to pay per night for each accommodation

[28] Online Appendix Table E15 shows that our ability to match observed market shares is similar in and out of sample.

Table 5—: Estimates of Selected Demand Parameters

	Random Coefficients Logit		Standard Logit	
Parameter	Estimate	Std. Error	Estimate	Std. Error
Log Google Trend	2.355	0.281	1.783	0.059
Price	-0.031	0.002	-0.025	0.001
Std. Deviation on Inside Option	1.725	1.060	.	.
Std. Deviation on Price	0.004	0.004	.	.

Note: This table displays the estimates and standard errors for selected parameters in travelers' utility (Equation 5).

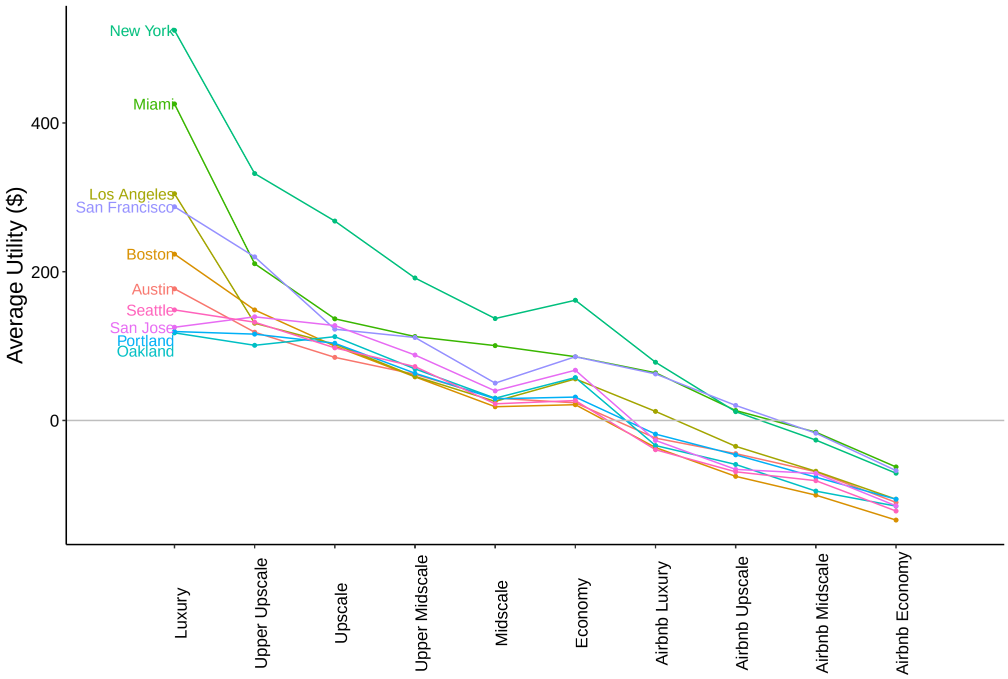
option and city at the end of 2014. The fact that some values are negative reflects our choice of a market size that is two times the average number of booked rooms in a city-month in 2012. When looking at the mean utilities in relative terms, our estimates show that willingness to pay tends to be decreasing between luxury and economy hotels and between Airbnb luxury and economy listings. The value of the top Airbnb option is lower than the value of the lowest hotel option across all cities, with some variation in the relative differences. We cannot distinguish between alternative explanations for this difference. Reasons for this may include people not having heard of Airbnb, business travelers often being unable to use Airbnb for their business travel, and Airbnb not offering complementary services such as concierge, 24-hour check-in, and daily cleaning. Within Airbnb options, distance to visitor centers in a city (a proxy of desirability for leisure travelers) is significantly correlated with consumers' willingness to pay (see Online Appendix D for more details).

We find that demand for accommodations is quite elastic, with an average price elasticity of -4.27 and substantial heterogeneity across cities and accommodation options. For example, in San Francisco, demand elasticities range between -8.63 for luxury hotels and -2.90 for the lowest-tier Airbnb listings.[29] The surprisingly large demand elasticity for luxury hotels is due to the fact that the limited consumer preference heterogeneity that we estimate does not completely offset the fact that demand elasticity is an increasing function of price, a well-known characteristic of logit demand systems. There is also substantial variation across cities in demand elasticities, ranging between -2.58 in Portland and -6.12 in New York for midscale hotels.

Next, we turn to the estimates of hotel cost parameters. Our parameter estimates are precise and the estimation procedure explains most of the variation with an R-squared of 0.79. The interquartile range for the errors is -\$14 to \$17. Figure 5 plots the marginal cost curves for different hotel tiers and cities at the end of 2014. We find that the constant components of hotels' marginal costs have the expected relationship with hotel quality. The marginal cost for luxury hotels

[29]Online Appendix Table E8 shows the city-specific elasticities of demand for different accommodations with respect to their own price and Online Appendix Table E9 shows the average cross-price elasticities.

Figure 4. : Estimated Utilities for Accommodation Options Across Cities



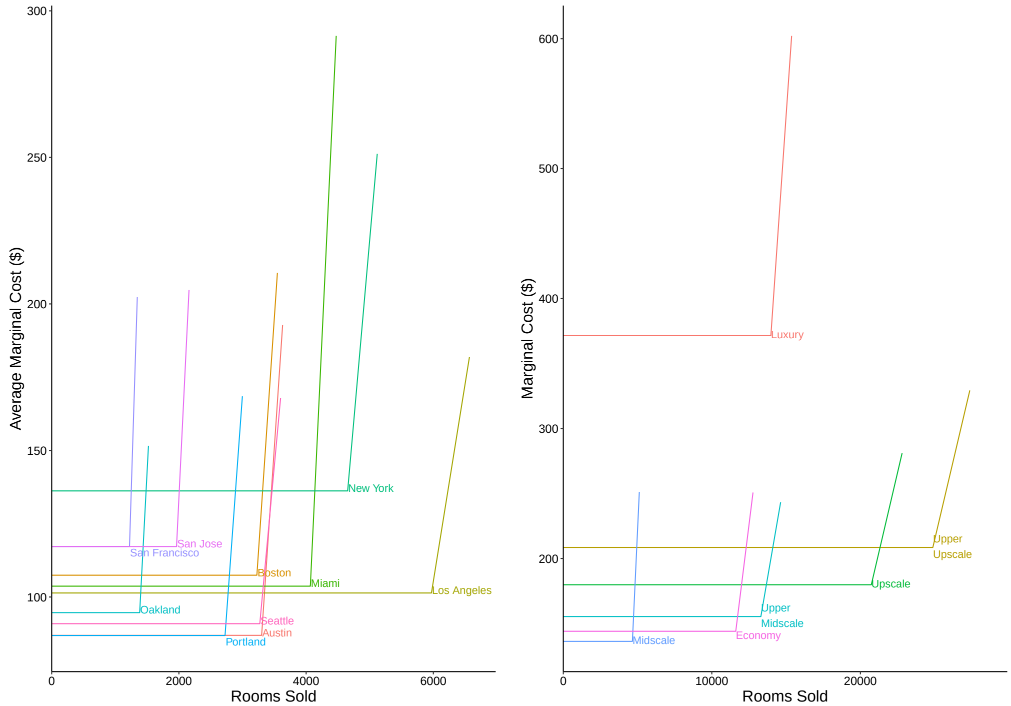
Note: This figure plots the estimated mean utilities for accommodation options across the 10 cities used in our estimation. The values are computed as averages over December 2014.

in New York city averages \$371, while this figure is \$144 for economy hotels. These costs should not, however, be interpreted as actual expenditures per night booked. Research by Kalnins (2006) suggests that, due to reputational concerns, hotels tend to enforce a minimum price threshold that is typically higher than the cost of an additional maid- or clerk-hour. We view our estimates as a reflection of this price threshold. The figure also plots the increasing component of hotels' marginal costs. In all city and hotel tier combinations, we find that marginal costs increase relatively steeply with quantity when hotel occupancy reaches 85%. This increasing cost reflects the fact that hotels will increase their prices as they approach full capacity regardless of the level of competition.[30] A comparison of these estimates with our reduced form results is reassuring. Indeed, the implied supply elasticities from these estimates are very close to our reduced-form estimates. The average supply elasticity across all markets and hotel tiers is 1, which is comparable to the reduced-form estimate of 1.3 from Table 3.

[30]Online Appendix Table E10 reports the estimated coefficients of Equation 10, with and without instruments. Online Appendix Tables E11 and E12 report the full set of cost estimates by city and hotel tier.

Figure 5. : Estimated Hotel Costs

(a) Costs by City – Midscale Hotels (b) Costs by Hotel Tier – New York City



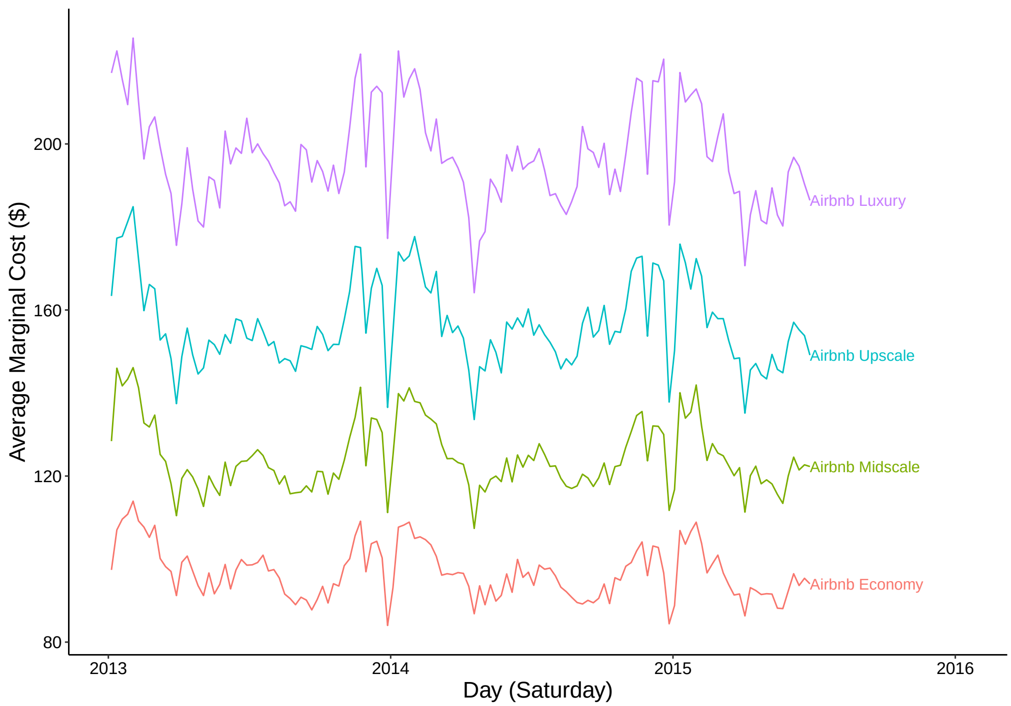
Note: These figures plot the estimated marginal cost curves of hotels across cities (left panel) and across quality tiers (right panel). The values are computed as averages over December 2014. Online Appendix Tables E11 and E12 display the cost estimates by city and hotel quality tier.

Finally, Figure 6 displays the mean costs over time for Airbnb listings in New York City. Costs vary over the course of the year, with higher costs during the winter season. Like other cities, costs in New York increase monotonically with listing quality, and the mean costs exceed the mean transacted prices. These relatively high costs stem from the fact that fewer than 50% of active listings on Airbnb typically get booked (Table 1).[31] With an R-squared of 0.42, the variation in our data is slightly less effective at explaining Airbnb costs than hotel costs. However, we estimate economically and statistically significant dispersion in the cost distribution for all listing types, which explains the high supply elasticity of Airbnb accommodations. As with the hotel estimates, the implied supply elasticities from the Airbnb cost estimates are very close to our reduced-form estimates. The average supply elasticity across all markets and listing types is

[31]Online Appendix Table E13 reports the estimated coefficients of Equation 11, with and without instruments. Online Appendix Table E14 displays the full set of estimates of Airbnb costs by listing type and city.

3.4. This is comparable to the reduced-form estimate of 3.9 in Table 3. The lowest-quality Airbnb listings are the most elastic, with an average supply elasticity of 4. Elasticity monotonically decreases as the listing quality increases, and top-quality listings have an elasticity of 3.1.

Figure 6. : Mean Costs of Airbnb Hosts in New York City



Note: The figures plot the estimated mean costs of Airbnb hosts in New York over time. Online Appendix Table E14 displays the estimated means and standard deviations by city and quality tier.

B. *Counterfactual Analysis*

Given these estimates, we perform three types of counterfactuals and measure differences between them and the status quo (*Baseline*). The first removes Airbnb in order to measure its welfare effects. The second type considers the effects of proposed regulatory policies. Finally, the third type of counterfactual explores the implications of additional Airbnb growth. Online Appendix C describes how we compute the counterfactual equilibria.

Our first counterfactual scenario (*Unconstrained*) looks at what would happen if Airbnb were removed but hotel prices remained constant and capacity constraints did not bind. In this scenario, travelers who booked on Airbnb are allowed to reserve any hotel option at the baseline prices, regardless of actual room availability. This allows us to measure how much better off consumers are simply because Airbnb offers a new set of options that are valued by at least some consumers. The second scenario (*No Airbnb*) allows hotels to adjust prices in response to the absence of competition from Airbnb listings. This counterfactual does take capacity constraints into account and involves the calculation of new Cournot equilibria for each market with demand and hotel cost parameters taken from our estimates.[32]

[32]The hotels' first order conditions (Equation 6) do not guarantee that, in the absence of Airbnb, equilibrium quantities remain below hotel capacity. In practice, however, capacity constraints are always satisfied when Airbnb does not exist and hotels reoptimize their choices under our parameter estimates.

Table 6—: Aggregate Surplus (MM)

	Consumers	Hotels			Peer Hosts			Government
	Change in Consumer Surplus	Rooms Sold	Revenues	Profits	Rooms Sold	Revenues	Peer Surplus	Lodging Taxes
Panel A: All markets in 2014								
Baseline		146	26,803	5,687	4.38	517	112	3,986
No Airbnb (Unconstrained)	-147	149	27,412	5,833				4,071
No Airbnb	-305	148	27,238	5,852				4,045
Airbnb With Lodging Tax	-65	146	26,891	5,718	3.47	377	82	4,058
Airbnb With Quotas	-157	147	27,106	5,754	1.49	181	40	4,027
Double Airbnb Rooms	130	145	26,630	5,623	6.18	672	146	3,962
Panel B: Compression Nights in 2014 (19.6% of all markets)								
Baseline		33	7,240	3,414	1.16	145	31	1,084
No Airbnb (Unconstrained)	-39	33	7,435	3,505				1,111
No Airbnb	-121	33	7,341	3,495				1,097
Airbnb With Lodging Tax	-24	33	7,258	3,429	0.94	107	23	1,103
Airbnb With Quotas	-14	33	7,256	3,424	1.01	125	28	1,086
Double Airbnb Rooms	53	33	7,199	3,380	1.65	190	41	1,078

Note: This table displays the outcomes for consumers, hotels, peer hosts, and local governments under the baseline scenario and five alternative scenarios: two scenarios without Airbnb and three scenarios with Airbnb and regulation. *'Unconstrained'* refers to the counterfactual scenario in which Airbnb options do not exist, hotels do not adjust prices and can accommodate any additional bookings regardless of their actual capacity. In the *'No Airbnb'* counterfactual, we let hotel prices readjust in response to the absence of Airbnb and accounting for hotel capacity constraints. The next counterfactuals consider new equilibrium prices and quantities under different regulation. The *'Airbnb with Lodging Tax'* counterfactual keeps Airbnb availability at the baseline level, but Airbnb travelers are charged the same lodging tax rate as hotel travelers. The *'Airbnb with Quotas'* counterfactual allows for Airbnb rooms to exist during the 90 days in a year with the largest number of travelers choosing to book accommodations in a particular city in the baseline scenario. For the other 275 days, Airbnb rooms are not allowed and so the equilibrium prices and quantities mirror those in the *'No Airbnb'* counterfactual. Note that those 90 days when Airbnb is allowed are not the same across all cities, but rather are determined independently for each city. The *'Double Airbnb Rooms'* counterfactual doubles the number of active Airbnb listings. Panel A displays metrics aggregated across all cities and nights in 2014 while Panel B focuses on compression nights, i.e., the markets when at least one hotel tier has an occupancy rate of 95% or more (19.6% of markets in 2014 are considered compression nights). All variables are in millions. For heterogeneity of the effects across cities, see Online Appendix Tables E16 through E18. For counterfactuals without consumer heterogeneity, see Online Appendix Table E20.

Table 6 presents the effects of removing Airbnb on consumers, hotels, and lodging taxes for all of 2014 (Panel A) and for so-called compression nights in 2014, i.e., nights when at least one hotel tier reaches 95% occupancy in the *Baseline* scenario (Panel B). Consumers would lose $147 million in surplus in the *Unconstrained* scenario. Given that 4.38 million rooms were booked on Airbnb in the baseline scenario, this loss corresponds to $33.60 per Airbnb room-night, about 16% of the average purchase price.[33] As mentioned, in this scenario consumer surplus loss is due entirely to a reduction in product differentiation.

Meanwhile, the *No Airbnb* counterfactual harms consumers through two additional mechanisms. First, travelers who booked on Airbnb but consider switching to a hotel now face higher hotel prices. Second, those who previously booked hotel accommodations also face higher prices. The consumer surplus loss in this scenario doubles, rising to $305 million. The vast majority of the difference between the *Unconstrained* and *No Airbnb* scenarios comes from inframarginal travelers who would book hotel rooms even if Airbnb were available. The price they face only increases by $1 on average (from $211 to $212), but 146 million travelers booked rooms in the *Baseline* scenario, resulting in a $155 million increase in expenditures for inframarginal travelers.[34] The remaining $3 million reduction in consumer surplus compared to the loss in the *Unconstrained* scenarios is due to the higher hotel prices facing those who consider switching from Airbnb.

There are two ways to think about the magnitudes of the effects on consumer welfare. On the one hand, peer production was responsible for just 3% of rooms sold in 2014 and, as a result, the surplus is small relative to the size of the market. Indeed, the combined 2014 revenues of hotels and peer hosts was $27.32 billion, meaning that the loss of consumer surplus is on the order of 1.1% of aggregate revenues. On the other hand, the benefits to individual consumers are substantial, with a consumer surplus benefit of $70 per Airbnb room night.

We now turn to the effects of Airbnb on hotels. In the *Unconstrained* scenario, hotels are able to increase rooms sold by 2% and revenues by 2.3%. The larger increase in revenues is because travelers book more Airbnb rooms when aggregate demand, and therefore average prices, are higher. If we take our cost estimates seriously, we can also look at the effect of Airbnb on hotel profits, which we calculate as hotel revenue minus the non-increasing part of the cost function. In the baseline scenario, profits amount to 21% of revenues, which seems to be a realistic figure. In the *Unconstrained* scenario, profits would increase by 2.5%. The ability to increase prices is what makes up for the capacity constraints and reduced occupancy in the *No Airbnb* counterfactual. Indeed, even though rooms sold and revenues only increase by 1.4% and 1.6% respectively, profits increase by 2.9% in the *No Airbnb* counterfactual, more than in the *Unconstrained* scenario.

Our estimates give us only a rough idea of the changes in hotel surplus for at

[33]Consumers' purchase price in the *Baseline* scenario, averaged across both hotel and Airbnb options, is $209.

[34]The loss is higher than $146 million because the price increases during compression nights are higher than during non-compression nights, which is also when relatively more rooms are booked.

least three reasons. First, hotels earn additional revenues through complementary services such as conferences and food sales, but also incur additional costs. Second, there are fixed costs involved in operating a hotel that we do not model. Third, our marginal cost estimates correspond in part to reputation costs rather than "true" marginal costs. Given these additional costs and revenues, we cannot state with certainty whether the hotel surplus is larger or smaller than our profit estimate.[35]

Not surprisingly, peer hosts would lose without Airbnb. We use the estimated cost distributions of hosts to back out the surplus that they receive from hosting on Airbnb. We truncate the cost distribution at zero, so the surplus for each day can be calculated as follows: $PS_{an} = \int_{-Inf}^{p_{an}} (p_{an} - max(c, 0)) dF_{an}(c)$. 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 on the platform. Table 6 displays the number of rooms sold, the total revenues, and host surplus. In the aggregate, peer hosts enjoy a producer surplus of \$112 million, or \$26 per room-night booked.

Welfare effects are even more pronounced during compression nights (Panel B of Table 6). Although compression nights represent only 19.6% of all markets, the reduction in consumer surplus on compression nights is 40% of the aggregate reduction in consumer surplus in the *No Airbnb* scenario. For hotels, increased profits on compression nights accounts for 49% of the aggregate profit increase that they would enjoy if Airbnb did not exist. The concentration of the effects during periods of high demand is not due to any preference for Airbnb on compression nights—these represent 26.5% of Airbnb baseline bookings and 26.7% of the reduction in consumer surplus from the *Unconstrained* counterfactual. Instead, the effect is due to hotels' capacity constraints. In fact, on compression nights, the number of hotel rooms sold in the *No Airbnb* scenario remains unchanged from the *Baseline* scenario at 33 million. But without Airbnb, hotel prices increase more during compression nights than during non-compression nights – an increase of \$2 versus \$0.60 – with sizable increases in revenue and profits as a result.

Since cities vary in their hotel room capacity relative to demand, the effects of Airbnb are geographically heterogeneous. In particular, since hotel capacity constraints are more often binding in New York and San Francisco, they would have proportionally larger reductions in consumer and peer host surplus and increases in hotel revenues and profits than cities like Portland or Miami in the absence of Airbnb.[36]

We also consider the extent to which Airbnb expands the market as opposed to

[35]In Online Appendix Table E17 we display the results assuming an alternative measure of costs for hotels imputed from the wage bill of hotels in our data and trends in the wages of maids across cities and over time. This is likely a lower bound on the true marginal cost of hotels.

[36]Online Appendix Tables E16 through E18 separate the effects of Airbnb on travelers, hotels, and peer hosts by city. Online Appendix Table E20 uses parameter estimates without consumer heterogeneity to replicate Table 6.

cannibalizing hotel demand. Online Appendix Table E19 displays results on the share of Airbnb travelers who would have booked a hotel room in the absence of Airbnb. In the *Unconstrained* scenario, between 29% and 33% of Airbnb bookings would not have resulted in a hotel booking, which is consistent with the substitution moment used to estimate demand. However, the market expansion effect becomes much larger when we account for capacity constraints and hotels' price responses. The share of Airbnb travelers who would not, in fact, have booked a hotel room increases across all cities, from 49% in Austin and Portland to 70% in New York, all the way up to 87% during compression nights.

We next explore what would happen to the accommodations market if Airbnb were subject to regulation. The first and most obvious regulation is lodging taxes (*Airbnb with Lodging Taxes*). In this scenario, Airbnb guests are charged a lodging tax rate equal to the rate charged to travelers staying at hotels. Note that for some markets, this scenario is identical to the *Baseline* since Airbnb already collects lodging taxes. For the vast majority of markets, however, this scenario implies an increase in the wedge between what the travelers pay and what the hosts receive. Implicitly, we assume that hosts do not pay lodging taxes out of their share of revenues in the *Baseline* scenario. To the extent that some hosts were already paying lodging taxes, these numbers should be considered an upper bound on the losses of peer hosts and travelers, and on the gains of hotels and local governments. Table 6 shows that, in this case, the reduction in consumer surplus is $65 million compared to *Baseline*, which represents only 21% of the consumer surplus loss from *No Airbnb*. This would allow local governments to increase tax revenues by about $72 million – a 1.8% increase – and hotels to increase revenues and profits by $88 million (0.3%) and $31 million (0.5%) respectively. Airbnb hosts, on the other hand, would see both their revenues and surplus decrease by 27% because 0.9 million fewer Airbnb rooms would be sold.

The second regulatory counterfactual considers quotas. Many local governments have proposed (and some have passed) regulations limiting the number of nights a listing can be booked within a calendar year without the host present at the residence. For example, San Francisco has set the maximum number of nights to 90, while Portland requires that a host reside in an Airbnb-listed residence for at least 270 days of the year, effectively capping the days that can be booked at 95 unless the host is present at the residence.[37] To proxy for this regulation, we consider a scenario (*Airbnb with Quotas*) in which all listings can only be booked 90 days per year, and we choose these days to coincide with the those on which the highest number of travelers book Airbnb or hotel accommodations in a given city. In other words, the *Baseline* scenario will apply in each city for the 90 days with the highest demand, with the *No Airbnb* counterfactual in effect on the remaining days. To the extent that Airbnb hosts cannot perfectly identify the high

[37]For the San Francisco regulation, see https://www.airbnb.com/help/article/871/san-francisco-ca. For Portland, see https://www.airbnb.com/help/article/875/portland-or. France has a similar regulation, https://www.airbnb.com/help/article/2108/night-limits-in-france-frequently-asked-questions. All websites were accessed January 2020.

demand days ahead of time, this scenario may overestimate Airbnb's benefits to consumers and peer hosts, particularly on the 90 days of high demand. On the other hand, because each host can choose when they host travelers independently of other hosts, and because there are no quotas if the host is present, this scenario is also likely to underestimate the benefits to consumers and peer hosts during the remaining 275 days in a year.

Table 6 shows that the consumer surplus losses would amount to 51% of the corresponding loss if Airbnb were completely banned. Because benefits are concentrated on high demand days, the consumer surplus loss would only be 12% of the surplus loss from the absence of Airbnb on compression nights. Hotels would not gain as much during compression nights, but the ban on Airbnb during non-compression nights would still allow them to increase revenues and profits by 1% compared to the baseline. Local governments would experience a 1% increase in taxes – levied on the travelers who would now stay in hotels during the low demand days of the year – which is about half of the tax revenue increase obtainable under the *Airbnb with Lodging Taxes* scenario. Peer hosts would only be allowed to sell 1.8 million rooms, obtaining about 35% of the revenues and surplus that they would obtain without regulation.

Finally, motivated by Airbnb's continued growth after our sample, we consider what would happen if Airbnb had twice as many active listings drawn from the same cost distribution that we estimated under the baseline scenario (*Double Airbnb Rooms*). This counterfactual estimates the effect of increasing Airbnb supply without changing the utility for these options. The effect of these additional rooms will be smaller than the removal of Airbnb because their main effect is to lower the prices of Airbnb rooms rather than adding additional options. These lower prices would attract travelers with a weaker preference for Airbnb relative to the first Airbnb guests, and would also put additional pricing pressure on hotels.

Table 6 shows that doubling Airbnb rooms would increase consumer surplus by $130 million. Comparing this to the $305 million loss in consumer surplus if Airbnb did not exist, it implies that the additional Airbnb supply would be about 43% as valuable as the initial supply. The further reduction in hotel revenues and profits is also around 40% of the effect of the initial Airbnb supply. For peer hosts, doubling Airbnb supply would increase their surplus by about 30% of the baseline supply level. In this counterfactual, Airbnb rooms do not completely replace hotels as the most common accommodations option, which is due to the much lower mean utilities that we estimate for Airbnb compared to hotels.

V. Conclusion

The spread of digital technology has enabled peer production in the accommodation industry. We study the welfare implications of this new mode of production for consumers, incumbent providers (hotels), and peer hosts.

The returns to peer production vary across cities and over time. Predictors of Airbnb penetration across cities include hotel room capacity, demand trends and volatility, and peers' costs of hosting strangers in their homes. Peer host supply is three times as elastic as hotel supply, rapidly expanding when demand and prices increase. The highly elastic host supply implies that the largest effects of Airbnb occur in markets where hotels are often near full capacity, which we confirm with reduced-form regressions. In particular, we show that Airbnb entry negatively affects hotel revenues in cities where hotels are more likely to be capacity-constrained, and that the effect is more concentrated on price than on quantity, at least compared to non-capacity-constrained cities.

Our descriptive facts provide intuition for the mechanisms at play when the peer supply of accommodations is allowed to compete with hotels. To quantify the welfare effects of peer supply, we present and estimate a model of competition between peer hosts and hotels. In addition to confirming the results from our reduced-form analysis, our estimates point to sizable benefits of peer supply. The availability of peer hosts generates \$305 million in consumer surplus in 2014 for the 10 largest US cities. About half of that surplus comes from consumers' heterogeneous preferences for accommodations, while the other half comes from competition that reduces prices and expands capacity when it is most needed. In addition, Airbnb generates \$112 million in peer host surplus in 2014, or \$26 per room-night.

Hotels are hurt because of competition with peer hosts. Without Airbnb, hotel revenues would be 1.6% higher, even if between 49% and 87% of nights booked on Airbnb would not have resulted in a hotel booking in the absence of Airbnb, with travelers choosing an alternative option, such as staying with friends or family or not traveling at all.

Our analysis informs the active policy debate regarding whether and how to regulate peer-to-peer accommodations. Proposed policies include fees and taxes, mandated registrations, quotas, caps on the number of nights per listing, and outright bans.[38] Our analysis suggests that Airbnb is especially beneficial to consumer and host welfare during peak demand periods in hotel-constrained cities. In fact, allowing Airbnb rooms to be booked just 90 days per year would recoup 49% of the consumer surplus loss from banning Airbnb outright. This indicates the desirability of a regulatory framework that preserves the benefits of peer production during peak demand periods. We also showed that parity in lodging taxes between peer hosts and hotels would raise an additional \$72 million in tax revenues while reducing consumer and peer host surplus by an amount equal to 23% of the loss that would occur if Airbnb were banned.

Airbnb has continued its rapid growth in both active listings and global awareness since the end of our data sample. Our model suggests that doubling Airbnb supply in 2014, holding everything else constant, would increase the baseline effects of 2014 supply on consumers and hotels by about 40% and the effect on peer hosts by about 30%. There are many aspects of Airbnb's growth that such

[38]See https://www.airbnb.com/help/article/1376/responsible-hosting-in-the-united-states.

a counterfactual does not capture. In particular, consumer utility for Airbnb listings may have changed over time due to changes in the composition of listings available and changes in the Airbnb platform.

We document two fundamental reasons why peer production is valuable in the accommodation industry, which can be generalized to cities that have experienced sizable growth in Airbnb listings. First, peers offer a differentiated product that is not a perfect substitute for hotel rooms and is valued by at least some consumers. Second, the hotel sector in many cities is frequently constrained by the limited number of available rooms, resulting in high prices during demand peaks because hotels cannot accommodate all potential travelers. Peer production expands available supply at exactly these times of peak demand, thus reducing hotel pricing power and increasing consumer surplus. To the extent that the supply of rooms on Airbnb has become more professionalized and fixed over time, our distinction of flexible versus dedicated capacity can be made not just between hotels and peer hosts, but within Airbnb across occasional and professional hosts.

Although our results concern the U.S. accommodation industry, our findings on the effects of peer entry can be applied more generally to industries such as transportation, food delivery, home services, and crafts. Consumer surplus increases because the entry of less professional, or peer providers, increases consumer choice and competition with existing, more professional providers. The competitive effect is particularly strong when existing providers have binding capacity constraints, which is more likely to be the case, for example, with taxis and ride-sharing than crafts or home services.

We have focused on the short-run effects of a peer-to-peer platform on the agents directly involved – hotels, peer hosts, and travelers. There are other parties involved in the market, who are also affected by peer entry, including the platform itself. Peer production can also have externalities and spillovers into other markets, including the labor and housing markets (Horton (2019), Barron, Kung and Proserpio (2018)). In the longer run, the number of hotel rooms and the composition of the housing stock is likely to adjust in response to peer entry. We leave the study of these important effects for future work.

REFERENCES

Aguiar, Luis, and Joel Waldfogel. 2018. "As streaming reaches flood stage, does it stimulate or depress music sales?" *International Journal of Industrial Organization*, 57: 278 – 307.

Airbnb. 2020. "Airbnb S1 Report."

Almagro, Milena, and Tomas Dominguez-Iino. 2020. "Location Sorting and Endogenous Amenities: Evidence from Amsterdam." *Working Paper.*

Andrews, Isaiah, Matthew Gentzkow, and Jesse M Shapiro. 2017. "Measuring the sensitivity of parameter estimates to estimation moments." *The Quarterly Journal of Economics*, 132(4): 1553–1592.

Barron, Kyle, Edward Kung, and Davide Proserpio. 2018. "The Sharing Economy and Housing Affordability: Evidence from Airbnb." *EC '18*, 5. New York, NY, USA:Association for Computing Machinery.

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.

Bolton, Gary, Ben Greiner, and Axel Ockenfels. 2012. "Engineering Trust: Reciprocity in the Production of Reputation Information." *Management Science*, 59(2): 265–285.

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.

Calder-Wang, Sophie. 2021. "The Distributional Impact of the Sharing Economy on the Housing Market." *SSRN Electronic Journal*.

Castillo, Juan Camilo. 2020. "Who Benefits from Surge Pricing?" *SSRN Electronic Journal*.

Chen, M. Keith. 2016. "Dynamic Pricing in a Labor Market: Surge Pricing and Flexible Work on the Uber Platform." *EC '16*, 455. New York, NY, USA:Association for Computing Machinery.

Cohen, Peter, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe. 2019. "Using Big Data to Estimate Consumer Surplus: The Case of Uber." , (22627).

Conlon, Christopher, and Jeff Gortmaker. 2020. "Best practices for differentiated products demand estimation with pyblp." *The RAND Journal of Economics*, 51(4): 1108–1161.

Conlon, Christopher T, and Julie Holland Mortimer. 2013. "Demand estimation under incomplete product availability." *American Economic Journal: Microeconomics*, 5(4): 1–30.

Cullen, Zoë, and Chiara Farronato. 2021. "Outsourcing Tasks Online: Matching Supply and Demand on Peer-to-Peer Internet Platforms." *Management Science*, 67(7): 3985–4003.

Einav, Liran, Chiara Farronato, and Jonathan Levin. 2016. "Peer-to-peer markets." *Annual Review of Economics*, 8: 615–635.

Einav, Liran, Chiara Farronato, Jonathan Levin, and Neel Sundaresan. 2018. "Auctions versus Posted Prices in Online Markets." *Journal of Political Economy*, 126(1): 178–215.

Expedia. 2019. “Expedia 10-k Report 2019.”

Filippas, Apostolos, John J Horton, and Richard J Zeckhauser. 2020. “Owning, Using, and Renting: Some Simple Economics of the “Sharing Economy”.” *Management Science*, 66(9): 4152–4172.

Fradkin, Andrey. 2019. “Search, Matching, and the Role of Digital Marketplace Design in Enabling Trade: Evidence from Airbnb.” *SSRN Electronic Journal.*

Fradkin, Andrey, Elena Grewal, and David Holtz. 2019. “The Determinants of Online Review Informativeness: Evidence from Field Experiments on Airbnb.” *SSRN Electronic Journal.*

Fraiberger, Samuel, and Arun Sundararajan. 2019. “Peer-to-Peer Rental Markets in the Sharing Economy.” *SSRN Electronic Journal.*

Friedman, James W. 1971. “A non-cooperative equilibrium for supergames.” *The Review of Economic Studies*, 38(1): 1–12.

Friedman, James W. 1977. *Oligopoly and the Theory of Games.* Vol. 8, North-Holland.

Griliches, Zvi. 1957. “Hybrid Corn: An Exploration in the Economics of Technological Change.” *Econometrica*, 25(4): 501–522.

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. 2019. “The Effects of Uber’s Surge Pricing: A Case Study.”

Horton, John J. 2014. “Misdirected Search Effort in a Matching Market: Causes, Consequences and a Partial Solution.” *EC ’14*, 357. New York, NY, USA:Association for Computing Machinery.

Horton, John J. 2019. “The Tragedy of Your Upstairs Neighbors: Is the Airbnb Negative Externality Internalized?”

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

Koulayev, Sergei. 2014. “Search for Differentiated Products: Identification and Estimation.” *The RAND Journal of Economics*, 45(3): 553–575.

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.

Lam, Tom, and Meng Liu. 2019. "Demand and Consumer Surplus in the On-Demand Economy: The Case of Ride Sharing."

Lewis, Greg, and Georgios Zervas. 2021. "The Welfare Impact of Consumer Reviews: A Case Study of the Hotel Industry." *Working Paper.*

Nosko, Chris, and Steven Tadelis. 2019. "The Limits of Reputation in Platform Markets: An Empirical Analysis and Field Experiment." , (20830).

Nowak, Brian, Thomas Allen, Jamie Rollo, Vaughan Lewis, Lin He, Ananda Chen, Wilson W. Ng, Michael Costantini, Owen Hyde, Kevin Liu, Mark Savino, Baset A. Chadhry, Anne M. Grube, and Ed Young. 2015. "Global Insight: Who Will Airbnb Hurt More - Hotels or OTAs?"

Petrin, Amil. 2002. "Quantifying the benefits of new products: The case of the minivan." *Journal of political Economy*, 110(4): 705–729.

Ryan, Stephen P. 2012. "The Costs of Environmental Regulation in a Concentrated Industry." *Econometrica*, 80(3): 1019–1061.

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.

Shapiro, Carl. n.d.. "Chapter 6 Theories of Oligopoly Behavior." In *Handbook of Industrial Organization.* Vol. 1, 329–414. Elsevier.

Zervas, Georgios, Davide Proserpio, and John W. Byers. 2017. "The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry." *Journal of Marketing Research*, 54(5): 687–705.