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

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ONLINE APPENDIX

Appendix A: Measures of Airbnb Supply

In this appendix, we demonstrate how to properly measure Airbnb supply. Figure A1 displays four measures of the size of Airbnb plotted over time: active listings, two measures of available listings, and booked listings. Active listings on a given day are those listings that are available to be booked for the same day or any future date. Available listings (unadjusted) are listings that are either booked for the day or listed as available to be booked on the same day. And booked listings are listings that have been booked for the day. This figure displays three important facts. First, the share of active or available listings that are booked varies greatly over time. The booking rate is especially high during periods of high demand such as New Year's Eve and the summer. What we will show in Section II.C is that this is the result of a highly elastic peer supply. Second, the gap between active listings and available listings is increasing over time, suggesting that over time more and more listings active on the website are not in fact available for rent to travelers – the share of active listings that are listed as available or booked on the day of stay drops from 77% in the first month of data to 65% in the last month of data. Therefore, the meaning of an active listing does not stay constant over the entire period of our study.[39]

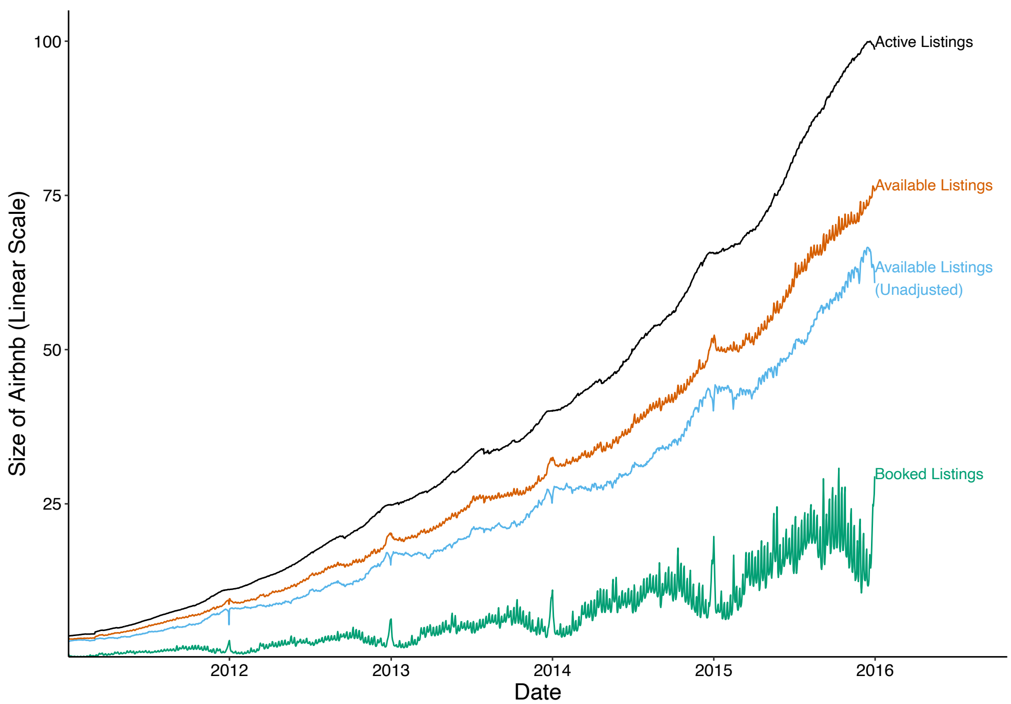
The third and most relevant fact from Figure A1 is that the number of unadjusted available listings actually decreases during periods of high demand, most notably on New Year's Eve. The main reason for this is that calendar updating behavior responds to room demand. Many hosts do not pro-actively take the effort to block a date on their calendar when they are unavailable (see Fradkin (2019) for evidence). However, when they receive a request to book a room, they often reject the guest and update their calendar accordingly. Since a larger share of listings receives inquiries during high demand periods, the calendar is also more accurate during those times. Therefore, the naively calculated availability measure suffers from endogeneity and is even counter-cyclical – high when demand is low, and low when demand is high.

Since we need a measure of the size of Airbnb that stays stable over time, we create an adjusted measure of available listings. This measure includes any rooms which were listed as available for a given date or were sent an inquiry for a given date and later became unavailable. Therefore, it does not suffer from the problem of demand-induced calendar updating. It does overstate the "true" number of available rooms in the market, but as long as it overestimates true availability

[39] Our definition of active listings does not correspond to the definition of active listings used in financial filings by Airbnb.

consistently over time we consider it to be the best measure of Airbnb size. Figure A1 displays our proposed measure (red line) against the naive measure of available listings (blue line). The new measure does not suffer from drops in availability during high demand periods. Throughout the paper and the appendices we use the adjusted number of available listings as the size of Airbnb supply, and we simply call them *available listings*.

Figure A1. : Measures of Airbnb Supply



Note: This figure plots four measures of the size of Airbnb. An active listing is defined as a listing available to be booked or booked for any future date. An (unadjusted) available listing is one that is either booked or has an open calendar slot on the date of stay. Available listings augment the unadjusted measure with listings that were contacted for a particular date of stay and were later updated to be unavailable for that date. A booked listing is one that has been booked for that date. The y-axis is normalized by the maximum number of active listings during our sample period to protect the company's proprietary data.

Appendix B: Theoretical Framework and Proofs

We present a theoretical model for understanding market structure with dedicated supply (hotels) and flexible supply (peer hosts) in the accommodation industry. It is a version of the model presented in Section III with more general demand and cost specifications, but with only one type of hotels and one type of Airbnb hosts. We prove existence and uniqueness of the equilibrium under certain conditions, as well as some comparative statics predictions that are corroborated by the stylized facts from Section II.

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

The Short-Run

We start with the short-run equilibrium representing daily market outcomes. We simplify the exposition by assuming that there is one single hotel and one undifferentiated type of Airbnb listings. Let h denote the hotel and a denote Airbnb. Further, let K_h denote the mass of existing dedicated capacity (number of available hotel rooms), and K_a the existing flexible capacity (available Airbnb rooms). Demand state, s, is drawn from a distribution $F(.)$, which can be interpreted as the distribution of demand states over the course of a year. Hotel rooms and Airbnb rooms are differentiated products. We denote $p_i^s(Q_i, Q_j)$ the inverse demand function for product i, which depends on the quantity for product i, product j, and demand state s. We assume that products i and j are substitutes, so $p_i^s(Q_i, Q_j)$ is decreasing in both Q_i and Q_j, and the prices of both products are increasing in the demand state.

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

$$\begin{array}{lc} \underset{Q_h}{Max} & Q_h \left(p_h^s(Q_h, Q_a) - c_h\right) \\ s.t. & Q_h \leq K_h \end{array} \tag{B1}$$

Flexible sellers have unit capacity and variable marginal costs of renting their room. We assume that marginal costs of peers are randomly drawn from a known distribution $G(.)$.

When choosing whether to rent out their room for a night, flexible producers take prices as given, and sell their unit if and only if the market clearing price is greater than their cost. The choices of individual hosts are aggregated to determine the total number of flexible rooms rented:

$$Q_a = K_a G\left(p_a^s(Q_h, Q_a)\right), \tag{B2}$$

where K_a is the mass of peer hosts, and $G\left(p_a^s(Q_h, Q_a)\right)$ is the share of hosts with costs lower than $p_a^s(Q_h, Q_a)$.

The market equilibrium consists of prices and quantities for hotel rooms and peer rooms that equate flexible and dedicated room demand with flexible and dedicated supply. For the proofs about the short-run equilibrium, we remove the superscript s, and denote hotel profits $\Pi = Q_h\left(p_h(Q_h, Q_a) - c_h\right)$.

The result of existence and uniqueness of the equilibrium is based on Friedman (1971) and Friedman (1977), and is equivalent to the stability requirement in Bulow, Geanakoplos and Klemperer (1985). Also see Shapiro (1989) for an overview of equilibrium in Cournot models.

PROPOSITION 1: *There is a unique equilibrium if the hotel's profit function is twice continuously differentiable, the hotel's marginal revenue curve does not rise with its own or its competitors' output, and*

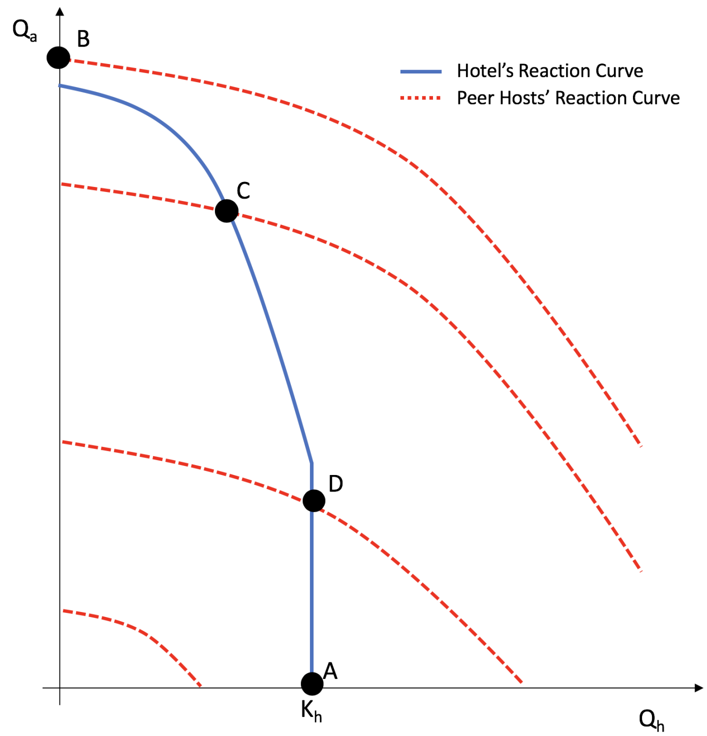
$$\frac{\partial^2 \Pi}{\partial Q_h^2}\left[K_a g(p_a)\frac{\partial p_a}{\partial Q_a} - 1\right] \geq \frac{\partial^2 \Pi}{\partial Q_h \partial Q_a} K_a g(p_a) \frac{\partial p_a}{\partial Q_h}.$$

Proof. Equilibrium is given by the intersection of the hotel and peer hosts' reaction curves (Fig. B1), determined by Equations B1 and B2. Under the condition in the proposition, both reaction curves are downward sloping, and we can prove that the hotel's reaction curve always has a slope smaller than the slope of the reaction curve of peer hosts. This ensures that the curves intersect at most once, either along one of the axes – where one type of supply sells zero rooms – or at an interior point where both suppliers sell rooms.

We first consider the case in which hotel capacity is not binding. The reaction curves are given by the following system of equilibrium equations:

$$\frac{\partial \Pi(Q_h, Q_a)}{\partial Q_h} = 0$$
$$K_a G\left(p_a(Q_h, Q_a)\right) - Q_a = 0.$$

Figure B1. : Equilibrium Quantities



Note: The figure plots the reaction curves, or best response functions, of the hotel and peer hosts. The hotel's reaction curve (solid line) is determined by the first order condition of its profit maximization problem, unless the optimum quantity is the maximum hotel capacity – vertical part of the solid line. The peer hosts' reaction curve (one of the four dotted lines) is determined by the equilibrium condition $K_a G(p_a) = Q_a$, where peer hosts take prices as given. Depending on the position of the peer hosts' reaction curve relative to the hotel's curve, the equilibrium is one of the four points denoted by A, B, C, or D.

Totally differentiating the system of equations leads to

$$\frac{\partial^2 \Pi}{\partial Q_h^2} dQ_h + \frac{\partial^2 \Pi}{\partial Q_h \partial Q_a} dQ_a = 0 \tag{B3}$$

$$K_a g(p_a) \frac{\partial p_a}{\partial Q_h} dQ_h + \left(K_a g(p_a) \frac{\partial p_a}{\partial Q_a} - 1 \right) dQ_a = 0. \tag{B4}$$

Equation B3 implies that the hotel's reaction curve has slope equal to $\frac{dQ_a}{dQ_h} = -\frac{\partial^2 \Pi}{\partial Q_h^2} \Big/ \frac{\partial^2 \Pi}{\partial Q_h \partial Q_a}$, while equation B4 implies that peer hosts' reaction curve has slope equal to $\frac{dQ_a}{dQ_h} = -K_a g(p_a) \frac{\partial p_a}{\partial Q_h} \Big/ \Big(K_a g(p_a) \frac{\partial p_a}{\partial Q_a} - 1 \Big)$.

The numerator and the denominator in both slopes are negative. For the slope of the hotel's reaction curve, this is because we have constant marginal costs and the hotel's marginal revenue curve does not increase with its own or its competitors' output. For the slope of the peer hosts' reaction curve, it is because for normal goods we have $\frac{\partial p_a}{\partial Q_a} \leq 0$, and substitutatibility implies $\frac{\partial p_a}{\partial Q_h} \leq 0$.

The slope of the hotel's reaction curve is smaller than the slope of its competitors' reaction curve whenever $-\frac{\partial^2 \Pi}{\partial Q_h^2} / \frac{\partial^2 \Pi}{\partial Q_h \partial Q_a} \leq -K_a g(p_a) \frac{\partial p_a}{\partial Q_h} / \left[K_a g(p_a) \frac{\partial p_a}{\partial Q_a} - 1\right]$. Reordering, the condition is equivalent to the condition in the proposition.

We now consider the case in which hotel capacity is binding, so $K_h - Q_h = 0$. In this case the hotel's reaction curve is vertical and crosses the x-axis (0 demand for Airbnb) at K_h. Regardless of whether the hotel's reaction curve hits its maximum room capacity before crossing the x-axis, the reaction curves of the hotel and of peer hosts will cross at most once at an interior point.

The unique equilibrium can be characterized as one of four options, as Fig. B1 shows. If the hotel's reaction curve is always below the reaction curve of peer hosts, the equilibrium will be along the y-axis, where the hotel sells no rooms. If the hotel's reaction curve is always above peer hosts' reaction curve, the equilibrium will be along the x-axis, where peers sell no rooms. Otherwise the equilibrium will be at the crossing point of the two reaction curves, where both suppliers sell some rooms, and the hotel can be either capacity-constrained or unconstrained. ■

The short-run model offers some comparative statics predictions. Under standard conditions, hotel profits per available room, as well as both prices and occupancy rates, are lower if K_a is higher. The separate effect of an increase in K_a on hotel prices is higher if hotel capacity constraints are more often binding, but the opposite is true for the effect on occupancy. Intuitively, this occurs because the increase in flexible capacity affects hotels through a reduction in their residual demand, and when hotels are capacity constrained, their supply curve is vertical. A marginal downward shift in residual demand will have no effect on quantity and a large effect on price if supply is perfectly inelastic (Figure B2). We present the propositions and the proofs below.

PROPOSITION 2: *Hotel profits and quantities weakly decrease in K_a. Hotel prices decrease in K_a if and only if* $\frac{\partial^2 \Pi}{\partial Q_h^2} \frac{\partial p_h}{\partial Q_a} - \frac{\partial^2 \Pi}{\partial Q_h \partial Q_a} \frac{\partial p_h}{\partial Q_h} \geq 0$.

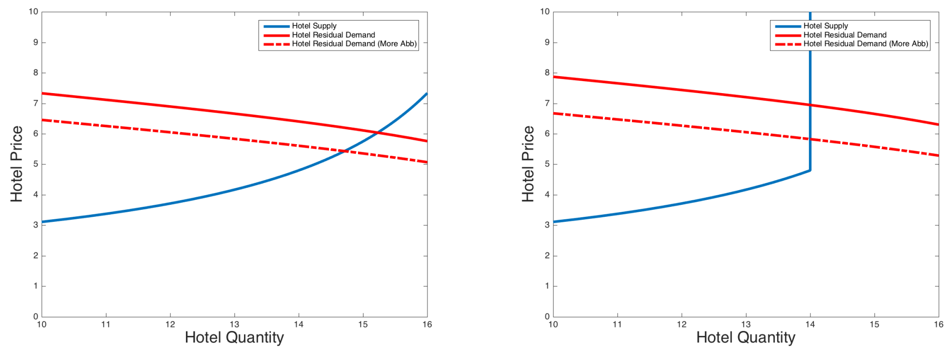
Proof. In order to prove Proposition 2 it is useful to separately consider markets where the hotel capacity constraint binds and markets where it does not. In markets where the hotel constraint binds the two equilibrium conditions are $Q_h = K_h$ and $Q_a = K_a G\left(p_a(Q_h, Q_a)\right)$. By totally differentiating the system of equilibrium equations we find the total derivatives of the hotel's and peer hosts' quantities with respect to peer hosts' capacity:

$$\left[\frac{dQ_h}{dK_a}\right]^c = 0 \tag{B5}$$

$$\left[\frac{dQ_a}{dK_a}\right]^c = \frac{-G(p_a)}{K_a g(p_a)\frac{\partial p_a}{\partial Q_a} - 1}. \tag{B6}$$

Figure B2. : Predictions on the Effect of Peer Supply on Hotels

(a) Unconstrained Equilibrium (b) Constrained Equilibrium



Note: The figures plot the supply and demand curve for hotel rooms in two scenarios. The hotel supply curve is drawn holding constant the price of peer rooms p_a, varying the demand state d, and letting the hotel set the price to maximize its profits as in Equation B1. The left panel displays an unconstrained equilibrium, while the right panel displays an equilibrium where the hotel capacity constraint is binding. Peer entry represents a downward shift in demand for hotel rooms. This downward shift will affect hotel quantity relatively more when the hotel supply curve is more elastic. The opposite is true for the effect on hotel prices, which is higher in the capacity-constrained equilibrium.

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

$$\left[\frac{dQ_h}{dK_a}\right]^u = \frac{G(p_a)\frac{\partial^2\Pi}{\partial Q_h \partial Q_a}}{\frac{\partial^2\Pi}{\partial Q_h^2}\left[K_a g(p_a)\frac{\partial p_a}{\partial Q_a} - 1\right] - \frac{\partial^2\Pi}{\partial Q_h \partial Q_a}K_a g(p_a)\frac{\partial p_a}{\partial Q_h}} \tag{B7}$$

$$\left[\frac{dQ_a}{dK_a}\right]^u = \frac{-G(p_a)\frac{\partial^2\Pi}{\partial Q_h^2}}{\frac{\partial^2\Pi}{\partial Q_h^2}\left[K_a g(p_a)\frac{\partial p_a}{\partial Q_a} - 1\right] - \frac{\partial^2\Pi}{\partial Q_h \partial Q_a}K_a g(p_a)\frac{\partial p_a}{\partial Q_h}}. \tag{B8}$$

We start by proving that hotel quantities are a decreasing function of flexible capacity in both constrained and unconstrained equilibria. Since in the constrained equilibrium the hotel quantity is fixed at its maximum capacity, its derivative with respect to flexible capacity is zero (equation B5). We simply need to prove that the derivative in equation B7 is negative. Again, this is directly implied by the conditions for existence and uniqueness of the equilibrium from Proposition 1. Indeed, the numerator is negative because hotel's marginal revenues are decreasing in peer hosts' quantity. The denominator is positive because of the condition in Proposition 1.

So far, we have proved that an increase in flexible capacity decreases hotel quantities by showing that $\frac{dQ_h}{dK_a} \leq 0$ whether or not the hotel is operating at capacity. Now we prove that an increase in flexible capacity also decreases hotel profits. An increase in K_a affects hotel profits $\Pi = Q_h(p_h - c_h)$ through changes in Q_h and Q_a:

$$\frac{d\Pi}{dK_a} = \frac{\partial \Pi}{\partial Q_h}\frac{dQ_h}{dK_a} + \frac{\partial \Pi}{\partial Q_a}\frac{dQ_a}{dK_a}.$$

Regardless of whether the hotel capacity constraint is binding, the first term in the summation is zero. If the hotel's capacity constraint is binding, it is because $\frac{dQ_h}{dK_a} = 0$ from equation B5. If the hotel's capacity constraint is not binding, it is because the hotel's first order condition holds with equality, so $\frac{\partial \Pi}{\partial Q_h} = 0$. The second term in the summation has the same sign as $\frac{\partial \Pi}{\partial Q_a}$ since $\frac{dQ_a}{dK_a}$ is positive regardless of whether the hotel's capacity constraint is binding (equations B6 and B8). Since $\frac{\partial \Pi}{\partial Q_a} = Q_h \frac{\partial p_h}{\partial Q_a}$ is negative because hotel and flexible rooms are substitutes, so is the derivative of hotel profits with respect to flexible capacity.

We are left with proving that an increase in flexible capacity also decreases hotel prices whenever $\frac{\partial^2 \Pi}{\partial Q_h^2}\frac{\partial p_h}{\partial Q_a} - \frac{\partial^2 \Pi}{\partial Q_h \partial Q_a}\frac{\partial p_h}{\partial Q_h} \geq 0$. An increase in K_a affects hotel prices through changes in Q_h and Q_a:

$$\frac{dp_h}{dK_a} = \frac{\partial p_h}{\partial Q_h}\frac{dQ_h}{dK_a} + \frac{\partial p_h}{\partial Q_a}\frac{dQ_a}{dK_a}.$$

In the case where the hotel capacity constraint is binding, the quantity derivatives with respect to K_a are given by equations B5 and B6. So the derivative of hotel prices with respect to flexible capacity simplifies to $\frac{dp_h}{dK_a} = -\frac{G(p_a)\partial p_h/\partial Q_a}{K_a g(p_a)\partial p_a/\partial Q_a - 1}$, which is always negative. In the case where the hotel capacity constraint is not binding, the quantity derivatives with respect to K_a are given by equations B7 and B8. After substitution, the derivative of hotel prices with respect to flexible capacity becomes

$$\frac{dp_h}{dK_a} = \frac{G(p_a)}{\frac{\partial^2 \Pi}{\partial Q_h^2}\left[K_a g(p_a)\frac{\partial p_a}{\partial Q_a} - 1\right] - \frac{\partial^2 \Pi}{\partial Q_h \partial Q_a}K_a g(p_a)\frac{\partial p_a}{\partial Q_h}}\left[\frac{\partial^2 \Pi}{\partial Q_h \partial Q_a}\frac{\partial p_h}{\partial Q_h} - \frac{\partial^2 \Pi}{\partial Q_h^2}\frac{\partial p_h}{\partial Q_a}\right].$$

The first ratio is always positive, so hotel prices decrease with flexible capacity if and only if $\frac{\partial^2 \Pi}{\partial Q_h^2}\frac{\partial p_h}{\partial Q_a} - \frac{\partial^2 \Pi}{\partial Q_h \partial Q_a}\frac{\partial p_h}{\partial Q_h} \geq 0$, which is the condition stated in the proposition. ■

PROPOSITION 3: *The reduction in hotel rooms sold when flexible capacity increases is larger when hotel capacity constraints do not bind. The reduction in hotel prices when flexible capacity increases is larger when hotel capacity constraints bind.*

The first part of proposition 3 is a trivial comparison of equation B5, which is always zero, and equation B7, which is never positive, and strictly negative when hotel's marginal revenue is strictly decreasing in competitors' quantity.

For the second part of the proposition, when hotel prices are a decreasing function of flexible capacity we want to prove that $\left[\frac{dp_h}{dK_a}\right]^c = \frac{\partial p_h}{\partial Q_a}\left[\frac{dQ_a}{dK_a}\right]^c \leq \left[\frac{dp_h}{dK_a}\right]^u = \frac{\partial p_h}{\partial Q_h}\left[\frac{dQ_h}{dK_a}\right]^u + \frac{\partial p_h}{\partial Q_a}\left[\frac{dQ_a}{dK_a}\right]^u$. Substituting equations B6, B7, and B8 gives

$$\frac{-\frac{\partial p_h}{\partial Q_a}G(p_a)}{K_a g(p_a)\frac{\partial p_a}{\partial Q_a}-1} \leq \frac{\frac{\partial p_h}{\partial Q_h}G(p_a)\frac{\partial \Pi^2}{\partial Q_h \partial Q_a} - \frac{\partial p_h}{\partial Q_a}G(p_a)\frac{\partial^2 \Pi}{\partial Q_h^2}}{\frac{\partial^2 \Pi}{\partial Q_h^2}\left[K_a g(p_a)\frac{\partial p_a}{\partial Q_a}-1\right] - \frac{\partial^2 \Pi}{\partial Q_h \partial Q_a}K_a g(p_a)\frac{\partial p_a}{\partial Q_h}}.$$

After some algebra the inequality simplifies to $K_a g(p_a)\left(\frac{\partial p_h}{\partial Q_h}\frac{\partial p_a}{\partial Q_a} - \frac{\partial p_h}{\partial Q_a}\frac{\partial p_a}{\partial Q_h}\right) - \frac{\partial p_h}{\partial Q_h} \geq 0$, which is always true because $\frac{\partial p_h}{\partial Q_h}\frac{\partial p_a}{\partial Q_a} - \frac{\partial p_h}{\partial Q_a}\frac{\partial p_a}{\partial Q_h} \geq 0$ when hotel's and peer hosts' rooms are substitutable,[40] and because $\frac{\partial p_h}{\partial Q_h} \leq 0$. ■

The Long-Run

In the long-run, entry of flexible suppliers, i.e. K_a, is endogenous. We assume that K_h is fixed.[41] We now let the price of each room option be a function of room quantities and the demand state, $p_a^s(Q_h, Q_a)$ and $p_h^s(Q_h, Q_a)$. Recall that we assume that both prices are an increasing function of the demand state and a decreasing function of both quantities. We simplify notation by writing p_a^s and p_h^s. We define the expected daily benefit of joining Airbnb as $v_a = \int_s E_c\left(max\{0, p_a^s - c\}\right) dF(s)$, and the one-time cost of joining as C, randomly drawn for each potential host. The expression $E_c\left(max\{0, p_a^s - c\}\right)$ denotes the expected per-period profit of a flexible seller given demand state s, where the expectation is taken over the distribution of marginal costs. We also let T denote

[40] When marginal costs are constant, substitutability between hotel's and peer hosts' rooms is defined equivalently as $\frac{\partial p_a}{\partial Q_h} \leq 0$ or $\frac{\partial Q_h}{\partial p_a} \geq 0$ (and analogously for hotel prices and peer hosts' quantities). Applying the implicit function theorem to the demand system $p_h(Q_h, Q_a) - p_h = 0$ and $p_a(Q_h, Q_a) - p_h = 0$ implies that the two are equivalent definitions of substitutability if and only if $\frac{\partial p_h}{\partial Q_h}\frac{\partial p_a}{\partial Q_a} - \frac{\partial p_h}{\partial Q_a}\frac{\partial p_a}{\partial Q_h} \geq 0$.

[41] Our model does not allow hotels to adjust dedicated capacity K_h in response to peer entry. Over many years, peer entry could partially crowd out dedicated sellers. Since our data only spans the first few years of Airbnb diffusion and hotel construction projects take between 3 and 5 years to complete, we are unable to empirically capture hotels' capacity adjustments. Exploring the entry and exit decisions of dedicated producers would be a valuable extension of our work.

the number of days a peer host will be available to host on Airbnb after joining the platform, so that the net benefit is $Tv_a - C$. We let K_a denote the mass of potential hosts who find it profitable to join Airbnb, i.e. all those hosts with $C \leq Tv_a$.

A peer-to-peer platform enables the entry of flexible sellers. Flexible sellers decide whether to join the peer-to-peer platform and start producing as a function of expected demand and expected marginal costs.

PROPOSITION 4: *Entry of flexible sellers is larger (K_a increases) if the distribution of peers' marginal costs c decreases in the sense of first-order stochastic dominance. K_a increases if K_h decreases. K_a increases if $F(s)$ increases in the sense of first order stochastic dominance. K_a also increases in response to a mean-preserving spread in $F(s)$ if peer hosts' prices are a convex function of s.*

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

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

Proving that a reduction in K_h induces more flexible entry requires a little more explanation. Assume K_h decreases on the margin. For demand states for which K_h was not binding, the decrease in hotel capacity has no effect, so p_a^s does not change for s lower than a certain threshold. For demand states in which K_h was binding the two equilibrium conditions are $Q_h = K_h$ and $Q_a = K_a G(p_a^s)$. We proved above (for Propositions 2 and 3) that an increase in flexible capacity decreases both hotel and peer prices. An analogous proof is valid for a change in hotel capacity. So for high demand states a decrease in hotel capacity increases flexible prices. So far we showed that in unconstrained demand states flexible prices do not change if K_h decreases, while in constrained demand states they increase. This is a shift in the distribution of flexible prices in the sense of first order stochastic dominance. So $\frac{dv_a}{dK_h} \leq 0$ and a decrease in hotel capacity induces more flexible entry.

Finally, a mean-preserving spread of $F(s)$ induces more entry of flexible sellers if p_a^s is a convex function of s.[42] The utility function for demand state s, $E_c\left[max\{0, p_a^s - c\}\right]$, is a convex function of p_a^s, so the result is a direct implication of Jensen's inequality. Intuitively, flexible sellers lose nothing from low demand periods since they can choose not to host, and gain high profits in periods of high demand. In order to verify whether p_a^s is a convex function of s, as before we totally differentiate the system of equilibrium equations $Q_a = K_a G(p_a^s)$ and $\frac{\partial \Pi^s}{\partial Q_h} = 0$ (which is $Q_h = K_h$ if hotels are capacity-constrained) with respect to the demand state and the quantity variables. We then note that $\frac{dp_a^s}{ds} = \frac{\partial p_a^s}{\partial s} + \frac{\partial p_a^s}{\partial Q_h}\frac{dQ_h}{ds} + \frac{\partial p_a^s}{\partial Q_a}\frac{dQ_a}{ds}$.

[42] Note that the sufficient condition that p_a^s is a convex function of s does not hold in general since it depends on both the shape of the demand curves as well as the distribution of peer costs.

When the hotel is not capacity constrained, the total derivative is equal to $\frac{dp_a^s}{ds} = \frac{-\frac{\partial p_a^s}{\partial s}\frac{\partial^2 \Pi}{\partial Q_h^2} + \frac{\partial p_a^s}{\partial Q_h}\frac{\partial^2 \Pi}{\partial Q_h \partial s}}{\frac{\partial^2 \Pi}{\partial Q_h^2}\left[K_a g(p_a^s)\frac{\partial p_a^s}{\partial Q_a} - 1\right] - \frac{\partial^2 \Pi}{\partial Q_h \partial Q_a} K_a g(p_a^s)\frac{\partial p_a^s}{\partial Q_h}}$, while when the hotel is capacity constrained the total derivative simplifies to $\frac{dp_a^s}{ds} = \frac{-\frac{\partial p_a^s}{\partial s}}{K_a g(p_a^s)\frac{\partial p_a^s}{\partial Q_a} - 1}$. Convexity of p_s^a in s requires that $\frac{dp_a^s}{ds}$ is non-decreasing in s, which depends on the shape of the demand curves and the distribution of peer costs. ■

Appendix C: Computational Details and Sensitivity Analysis

In this section we describe our computational procedure to estimate the model and compute the equilibrium, as well as a sensitivity analysis of our demand estimates presented in Table 5.

To estimate the demand model, we use the PyBLP package (Conlon and Gortmaker (2020)) with some minor modifications to allow for our substitution moment. We use the KNITRO solver with a tolerance of 10^{-5} and the product rule of degree 7 to estimate the main specification. The estimates are robust to a variety of starting points. We use a 1-step procedure in order to set the relative weight on the substitution moment relative to the market share moments.[43]

We use several strategies for conducting sensitivity analysis. The first strategy is to compute estimates from our model using alternative values of the substitution moment (Equation 9). This would be useful if one were concerned that our estimate of the substitution to the outside option, which we set at 32% given Airbnb survey data, was biased. We choose two comparison values, one value that implies that an additional 10% of Airbnb travelers would substitute towards the outside option if Airbnb did not exist and another value that implies that 10% fewer Airbnb travelers would choose the outside option. We report the results in Table C1. With less substitution to the outside option, the random coefficient on the inside option would increase, as expected. Similarly, with more substitution to the outside option, the random coefficient on the inside option would decrease. As the table shows, changes in the substitution moments affect the estimates of other parameters such as price sensitivity, albeit less.

We can do a similar analysis to measure how our instruments help us identify the linear coefficient on price. To do so, we estimate the logit specification without consumer preference heterogeneity in four ways: with all our instruments combined, with each type of instrument separately, and without any instruments. The results from these estimates are displayed in Figure C1. Each set of instruments yield negative estimates for the price coefficient, in sharp contrast to the non-IV estimate, but the magnitude and precision vary. The price estimate from using all instruments jointly lies in the middle of the range of the IV estimates and is more precisely estimated than any of them.

Andrews, Gentzkow and Shapiro (2017) propose an approach to evaluate the sensitivity of our estimates to assumptions based on local perturbations. To measure sensitivity, we compute the sensitivity matrix $\Lambda = -(G * W * G)^{-1} G * W$ where G is the Jacobian of the moments with respect to the non-linear parameters and W is the weighing matrix. There are two types of moments. The first set, standard in Berry, Levinsohn and Pakes (1995), includes the linear IV moments

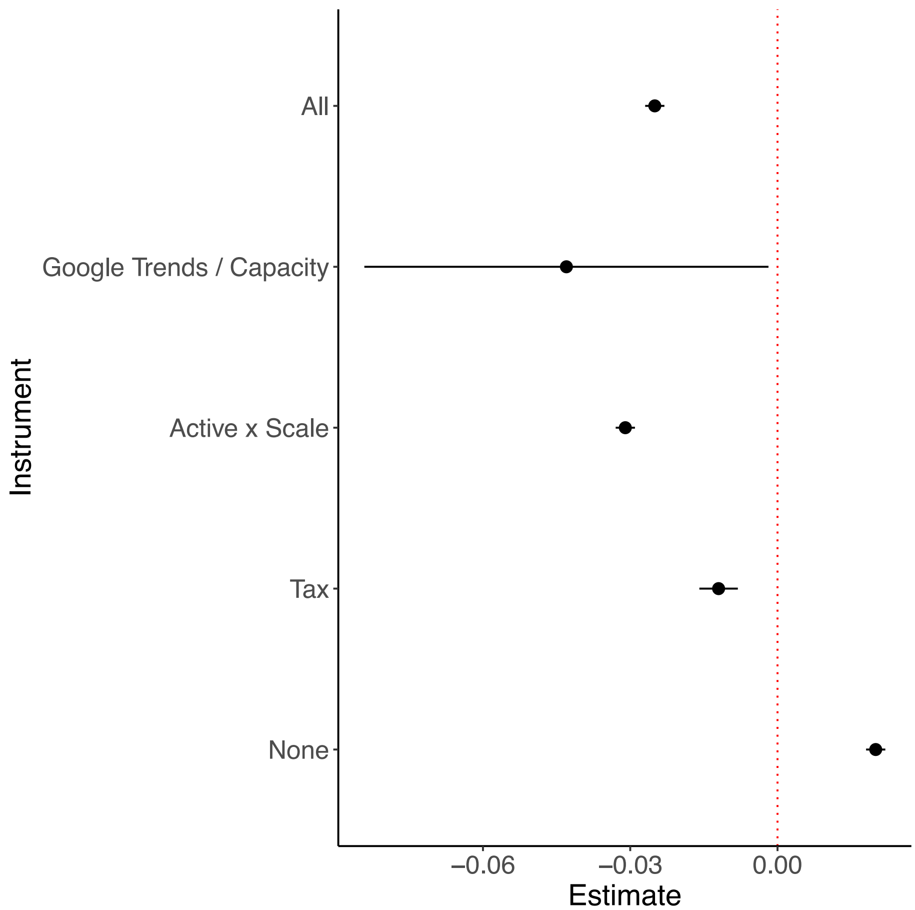
[43]The weighing matrix is block diagonal, with $(\hat{Z}'\hat{Z})^{-1}$ in the top left and the substitution moments in the bottom right. $\hat{Z}$ is the set of instruments, with the fixed effects for month-city-tier and day of week partialed out. PyBLP does this by using the Python package 'pyhdfe' to run a regression of each column on the fixed effects and producing the residuals. This is a computational trick used to increase the speed of computation when there are many fixed effects.

(Equation 8). The second set includes the substitution moment from Equation 9. We multiply Λ by $(\hat{Z}'\hat{Z})^{-1}$ for the linear IV moments and by $1/N$, where N is the number of markets, for the substitution moment.

We report this sensitivity measure in Figure C2 denoted as 'Raw.' We follow Andrews, Gentzkow and Shapiro (2017) in scaling the raw estimates by the inverse of the standard deviation of $\hat{Z}$ for each instrument. For the substitution moment, we scale it so that the sensitivity represents the response to an increase of .1 in the share of Airbnb travelers who would substitute to the outside option if Airbnb did not exist. All of the moments help to identify the non-linear parameters, as expected. We see that the implied change in the random coefficient on the constant due to a change in the substitution moment is within an order of magnitude of the changes we observed by re-estimating the model with different values of the substitution moment. We also see that the price coefficient is highly sensitive to the ratio of the Google Search Trends to capacity.

Finally, we describe some details to compute the equilibrium with our parameter estimates under different scenarios. We use a trust region reflective algorithm within the fsolve function in Matlab. We find a price vector that solves a system of hotel and Airbnb equations. The hotel equations, one per hotel tier, come from their first order conditions (Equation 6). The Airbnb equations, one per Airbnb options, come from the equilibrium condition in Equation 7, which allows us to find the price that rationalizes a particular number of booked listings. For a candidate price vector, we first find demand, which allows us to compute the markup in Equation 6 and Airbnb rooms sold in Equation 7. The algorithm then minimizes the difference between the candidate price vector and the prices implied by the supply equations. We use the baseline prices as our initial starting values. When the sum of the absolute price deviations across all options is bigger than 1e-7 we try two more starting values: one with prices that are 6.7% higher than the baseline prices, and the other with prices that are 13.3% higher. Out of these attempts, we select the solution with the lowest sum of absolute price deviations across all options.

Figure C1. : Sensitivity of Logit Estimates to Instruments



Note: The figure plots the estimated price coefficients and the 95% confidence intervals for the demand model without consumer preference heterogeneity under five instrumentation options: using all our instruments, using only the Google search trends divided by room capacity, using only room capacity interacted with accommodation option fixed effects, using only tax rates, and using no instruments for price. 'All' refers to the logit specification in the paper, which is shown in column 2 of Table 5.

Table C1—: Estimates of Selected Demand Parameters - Varying Substitution to Outside Option Moment

	Share to OO = .32		Share to OO = .22		Share to OO = .42	
Parameter	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Log Google Trend	2.355	0.281	2.646	0.585	2.151	0.156
Price	-0.031	0.002	-0.029	0.003	-0.031	0.002
Std. Deviation on Inside Option	1.725	1.060	2.902	2.617	0.789	0.756
Std. Deviation on Price	0.004	0.004	0.002	0.007	0.004	0.004

Note: This table displays the estimates and standard errors for selected parameters in travelers' utility. The first reproduces the estimates in column 1 of Table 5, which assume that 32% of Airbnb bookings would have gone to the outside option if Airbnb did not exist. The second column assumes the substitution to the outside option is instead 22% and the third column assumes the substituion to be 42%.

Table C2—: Sensitivity of Random Coefficient to Estimation Moments

Moment Moment	Raw - Constant	Scaled - Constant	Raw - Price	Scaled - Price
Survey Moment	57.31	5.73	-0.63	-0.06
Google Trend / Capacity	-0.00	-10.70	0.00	0.27
Tax Rate	-0.02	-2.07	-0.00	-0.06
Active: Luxury	25.94	0.37	-6.60	-0.09
Active: Airbnb Midscale	-307.06	-2.17	-4.89	-0.03
Active: Airbnb Economy	-289.37	-2.67	-1.67	-0.02
Active: Upper Upscale	2.81	0.03	-6.37	-0.08
Active: Upscale	-60.51	-0.36	-13.86	-0.08
Active: Upper Midscale	-119.58	-1.53	-5.26	-0.07
Active: Midscale	20.03	0.89	-1.02	-0.05
Active: Economy	31.16	0.62	1.50	0.03
Active: Airbnb Luxury	-107.59	-0.36	-23.68	-0.08
Active: Airbnb Upscale	-235.12	-1.45	-8.49	-0.05
Log Google Trend	-1.44	-17.43	0.00	0.05
Austin/TX Hotel X Time	-37.90	-4.01	-0.66	-0.07
Austin/TX Airbnb X Time	-14.72	-2.77	-0.08	-0.02
Boston/MA Hotel X Time	-55.08	-5.82	0.43	0.05
Boston/MA Airbnb X Time	-5.72	-1.05	-0.21	-0.04
Los Angeles/Long Beach/CA Hotel X Time	-80.13	-8.47	1.06	0.11
Los Angeles/Long Beach/CA Airbnb X Time	-13.35	-1.74	-0.30	-0.04
Miami/Hialeah/FL Hotel X Time	-14.26	-1.51	-0.42	-0.04
Miami/Hialeah/FL Airbnb X Time	1.28	0.18	-0.41	-0.06
New York/NY Hotel X Time	-12.47	-1.32	-0.98	-0.10
New York/NY Airbnb X Time	-22.84	-2.96	-0.36	-0.05
Oakland/CA Hotel X Time	-71.75	-7.59	0.36	0.04
Oakland/CA Airbnb X Time	-10.19	-2.48	-0.04	-0.01
Portland/OR Hotel X Time	-92.35	-9.77	0.82	0.09
Portland/OR Airbnb X Time	-20.15	-3.77	0.02	0.00
San Francisco/San Mateo/CA Hotel X Time	-16.85	-1.78	-0.26	-0.03
San Francisco/San Mateo/CA Airbnb X Time	14.02	1.82	-0.79	-0.10
San Jose/Santa Cruz/CA Hotel X Time	-33.18	-3.51	-0.33	-0.03
San Jose/Santa Cruz/CA Airbnb X Time	-3.46	-0.81	-0.19	-0.04
Seattle/WA Hotel X Time	-69.64	-7.36	0.41	0.04
Seattle/WA Airbnb X Time	-9.98	-2.19	-0.08	-0.02

Note: This table displays the sensitivity values of Andrews, Gentzkow and Shapiro (2017) for our substitution moment and for the instruments residualized by the fixed effects included in the demand model. The column 'Scaled' scales the values of 'Raw'. This is scaled by .1 in the case of the survey moment, which represents a change of .1 in the substitution to the outside option. It is scaled by the standard deviation of the residualized instruments for the other rows.

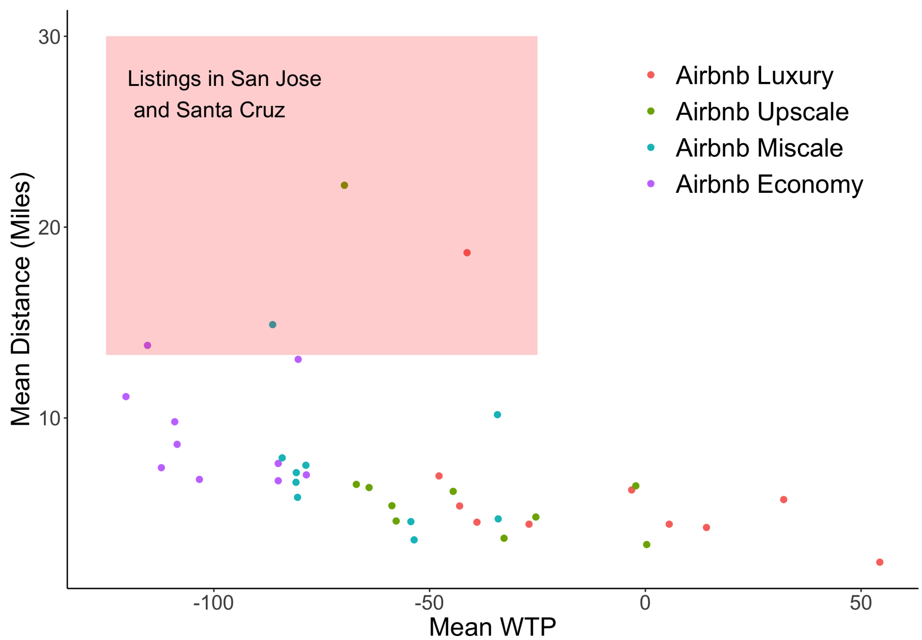
Appendix D: The Role of Location in Determining Mean Utilities

In this section we describe some results regarding the importance of location in determining the value consumers place on each accommodation type. In order to measure the 'quality' of a location, we measure its distance to visitor centers in a city. The implicit assumption is that visitor centers are located close to points of interest for leisure travelers. For each city, we find up to three top listed visitor centers according to searches on Google for 'visitor centers' in that city. Separately for each listing and hotel we calculate its distance from the closest visitor center. Finally, we aggregate the data to the tier level by taking a weighted average across all options within that accommodation category. Note that for hotels, since we do not have sales at the hotel level, we weigh each hotel by the number of available listings. For Airbnb, since we compute this distance before aggregating, we weigh listings by transactions.

We report two main findings. First, the willingness to pay of travelers for Airbnb options is decreasing in their distance from the closest visitor center. Figure D1 plots the average willingness to pay in December of 2014 against the average distance in miles. We see that better Airbnb options ('Airbnb Luxury') have a higher willingness to pay and a lower distance to visitor centers. There are several outliers, which are listings in San Jose and Santa Cruz, likely caused by the fact that leisure travel demand in this market comes from rural locations rather than urban areas. To measure the correlation, we can run a simple linear regression where the outcome variable is willingness to pay and the explanatory variable is distance to the closest visitor center. We find a negative and statistically significant relationship (Table D1). Each additional mile is associated with a $4.17 decrease in willingness to pay.

Our second finding is that hotels are often further from visitor centers than Airbnb listings. In Figure D2 we plot the average distance between hotels and the closest visitor center (triangles) as well as the average distance between Airbnb options and the closest visitor center (circles). We find that hotel options are often much further away from the visitor center than booked Airbnb options, although this varies by city and hotel type. Higher quality hotel options are located closer to the visitor center. Part of the difference in location is explained by the different weights (available versus booked rooms), but most of it is likely explained by the fact that many hotels cater to business travelers, who may want to stay close to airports, and in business districts that are not always close to tourist attractions. At the same time, luxury hotels are more likely to serve leisure travelers and are therefore located close to the most desirable places for visitors in a city.

Figure D1. : Willingness to Pay and Proximity to Tourist Attractions



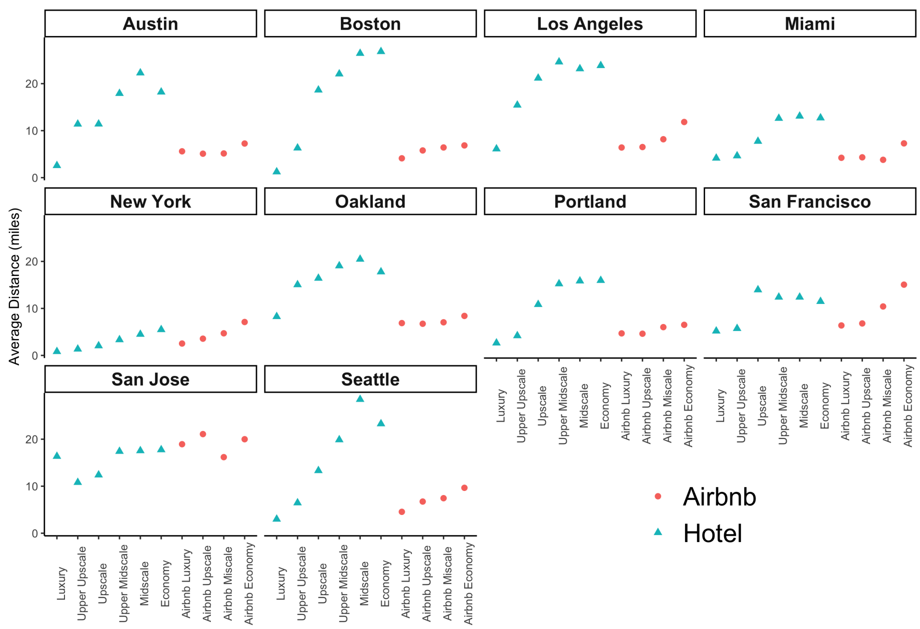
Note: The figure plots the estimated willingness to pay for an option against the average distance between booked listings and the closest visitor center. Options for San Jose/Santa Cruz are highlighted in red as outliers.

Table D1—: Willingness to Pay and Proximity to Tourist Attractions

+ 1em		+ 1em	WTP
+ 1em	Constant	+ 1em	-16.050
+ 1em		+ 1em	(15.848)
+ 1em	Mean Distance (miles)	+ 1em	-4.174**
+ 1em		+ 1em	(1.613)
+ 1em	N	+ 1em	40
+ 1em	R2	+ 1em	0.130

Note: This table displays a regression of the willingness to pay for each Airbnb option on the average distance to the closest visitor center.

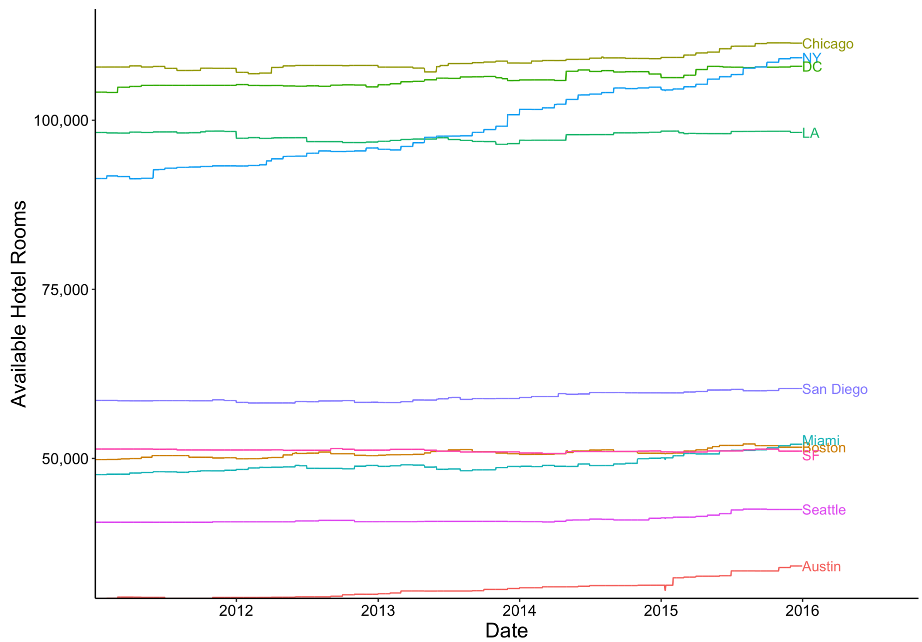
Figure D2. : Proximity to Tourist Attractions by City and Tier



Note: The figure plots the average distance to the closest visitor center for each accommodation option and city.

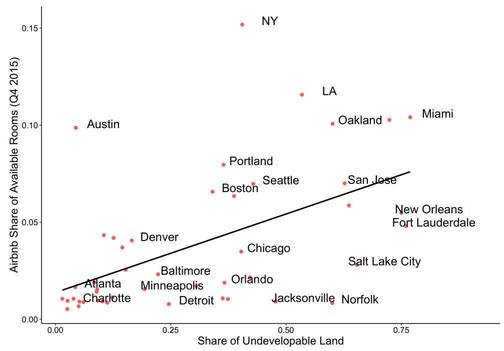
Appendix E: Additional Figures and Tables

Figure E1. : Hotel Rooms

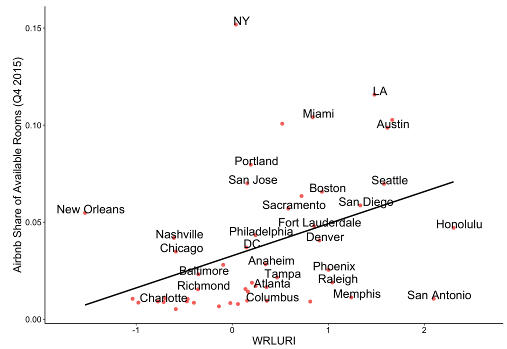


Note: The figure plots hotel room capacity over time for the top 10 cities. In contrast to the growth of Airbnb (Figure 1), the number of hotel rooms has been relatively stable over this time period.

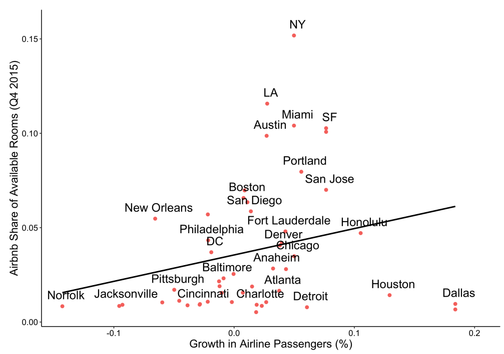
Figure E2. : Predictors of Peer Production



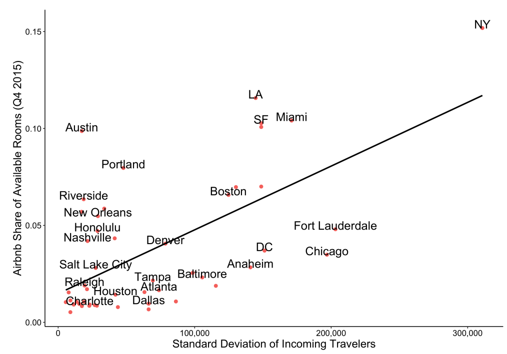
(a) Share of Undevelopable Land



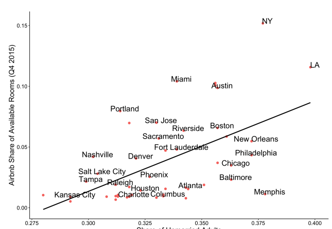
(b) WRLURI



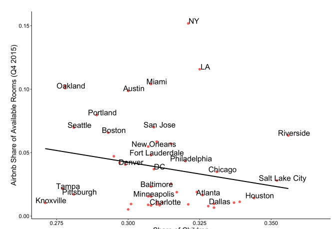
(c) Demand Growth



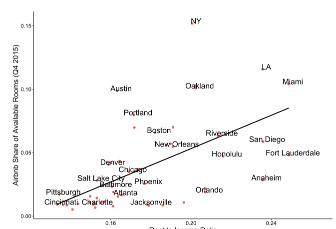
(d) Demand Variability



(e) Share of Unmarried Adults



(f) Share of Children



(g) Housing Costs

Note: The figures plot the size of Airbnb against proxies for accommodation costs and demand characteristics. The size of Airbnb is measured as the average share of available rooms in the last quarter of 2015. Panel (a) focuses on the share of undevelopable area developed by Saiz (2010), which measures the share of a city that is undevelopable due to geographic constraints, like steep mountains or the ocean. Panel (b) uses the Wharton Residential Land Use Regulation Index, which measures the stringency of the local regulatory environment for housing development, which we consider to be similar for commercial buildings. Panel (c) plots Airbnb share against the growth rate in incoming air passengers to an MSA between June 2011 and June 2012. Panel (d) uses the standard deviation of air travelers from 2011 monthly data on arriving passengers at major US airports. Panel (e) proxies for peers' marginal costs with the share of unmarried adults in the Metropolitan Statistical Area (MSA) and Panel (f) with the share of children. Finally, Panel (g) plots the size of Airbnb against the ratio of median rent to household income in the MSA in 2010. The fitted lines weigh each city equally.

Table E1—: Descriptive Statistics of Predictors of Airbnb Penetration

Statistic	N	Mean	St. Dev.	25 Pct	Median	75 Pct
WRLURI	50	0.30	0.84	−0.36	0.20	0.85
Share of Undevelopable Area	46	0.30	0.24	0.09	0.23	0.43
Percent Never Married	48	0.33	0.03	0.31	0.33	0.36
Share of Children	48	0.31	0.02	0.30	0.31	0.32
Rent to Income Ratio	50	0.18	0.03	0.15	0.17	0.20
Std Dev of Google Trend	50	12.05	4.22	9.62	11.51	13.70
Std Dev of Incoming Passengers ('0,000s)	50	6.62	6.31	1.80	3.93	10.82
Passengers' Growth	50	0.02	0.06	−0.02	0.01	0.04

Note: The table shows descriptive statistics on market characteristics for the 50 cities in our sample. The WRLURI and Saiz's share of undevelopable area are proxies for constraints to hotel supply (see Gyourko, Saiz and Summers (2008) and Saiz (2010)). The share of children and unmarried adults proxy for hosting costs of Airbnb hosts, and are retrieved from the Census Bureau (https://www.census.gov/data.html). The standard deviation of Google trends and incoming passengers, computed in 2011, are two measures of demand volatility and are obtained from Google Trends (https://trends.google.com) and Sabre Travel Solutions, the largest global distribution systems provider for air bookings in the US. The growth in airline passengers is computed from Sabre data for 2012 relative to 2011.

Table E2—: The Supply Elasticity of Hotels and Peer Hosts – First Stage Estimates

	log(Hotel Price)	log(Airbnb Price)	log(Airbnb Available Listings + 1)
	(1)	(2)	(3)
log(Incoming Air Passengers)	0.479***	0.38	-0.09***
	(0.041)	(1.142)	(0.014)
log(Incoming Google Searches)	0.11***	0.062	-0.009
	(0.025)	(0.785)	(0.009)
log(Hotel Rooms + 1)	-0.252*		
	(0.134)		
log(Airbnb Active Listings + 1)		0.11	0.962***
		(0.807)	(0.015)
Observations	90,900	84,959	84,959
R^2	0.854	0.578	0.999

Note: First stage results of Table 3. Column (1) is the first stage of column (1) from Table 3. Columns (2) and (3) are the first stage of column (2). Standard errors are clustered at the city level. *p<0.1; **p<0.05; ***p<0.01. In both cases, we reject the hypotheses of under and weak identification, and reject that the joint set of instruments is not valid. For the first column, the Kleibergen-Paap LM statistic is 10.6 (p-value of 0.0049), the Kleibergen-Paap Wald F statistic is 109.5, and the Hansen J statistic is 0.11 (p-value of 0.7443). For the second and third column jointly, the Kleibergen-Paap LM statistic is 16.4 (p-value of 0.0003), the Kleibergen-Paap Wald F statistic is 44.44, and the Hansen J statistic is 0.995 (p-value of 0.3185).

Table E3—: The Supply Elasticity of Hotels and Peer Hosts – OLS

	Log(Hotel Rooms Boooked + 1)	Log(Airbnb Rooms Booked + 1)
	(1)	(2)
log(Hotel Rooms + 1)	0.628***	
	(0.187)	
log(Hotel Price)	1.063***	
	(0.058)	
log(Airbnb Available Listings + 1)		0.696***
		(0.050)
log(Airbnb Price)		0.689***
		(0.071)
City FE	Yes	Yes
Year-Month FE	Yes	Yes
Day of Week FE	Yes	Yes
Observations	91,250	85,146
R^2	0.956	0.950

Note: OLS regression results of Equation 2. Otherwise the table is identical to Table 3. The number of observations is higher than in Table 3 because of our instrumentation strategy that uses lagged values. Standard errors are clustered at the city level. *p<0.1; **p<0.05; ***p<0.01.

Table E4—: Hotel Revenues and Airbnb Entry – First Stage Estimates

	log(Airbnb Available Listings + 1) (1)	log(Airbnb Available Listings + 1)* Inelastic Housing Supply (2)
log(Airbnb Active Listings + 1)	0.943***	0.001
	(0.023)	(0.022)
log(Airbnb Active Listings + 1)* Inelastic Housing Supply	0.066**	1.007***
	(0.026)	(0.31)
log(Incoming Air Passengers)	-0.084***	-0.04
	(0.012)	(0.35)
log(Incoming Google Searches)	-0.017*	-0.003
	(0.009)	(0.143)
log(Hotel Rooms + 1)	-0.063	0.069
	(0.299)	(0.537)
log(Hotel Rooms + 1)* Inelastic Housing Supply	0.047	-0.126
	(0.317)	(2.825)
Observations	90,900	90,900
R^2	0.999	1

Note: First stage results of Table 4. All columns in Table 4 have the same first stage regressions. Standard errors are clustered at the city level. *p<0.1; **p<0.05; ***p<0.01. With a Kleibergen-Paap LM statistic of 27.2 and Wald F statistic of 1,802.3, we reject the hypotheses of under and weak identification.

Table E5—: Hotel Revenues and Airbnb Entry – OLS

	Log(RevPAR)	Occupancy Rate	Log(Price)
	(1)	(2)	(3)
log(Incoming Air Passengers)	1.103***	0.370***	0.481***
	(0.063)	(0.041)	(0.040)
log(Google Search Trend)	0.246***	0.077***	0.109***
	(0.042)	(0.012)	(0.024)
log(Hotel Rooms + 1)	−0.933***	−0.520***	−0.088
	(0.326)	(0.138)	(0.168)
log(Hotel Rooms + 1)*	−0.562	0.021	−0.660**
Inelastic Housing Supply	(0.371)	(0.168)	(0.287)
log(Airbnb Available Listings + 1)	0.022	−0.004	0.027**
	(0.023)	(0.009)	(0.012)
log(Airbnb Available Listings + 1)*	−0.086***	−0.011	−0.074***
Inelastic Housing Supply	(0.032)	(0.012)	(0.023)
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	0.592	0.856

Note: OLS regression results of Equation 3. Otherwise the table is identical to Table 4. Standard errors are clustered at the city level. *p<0.1; **p<0.05; ***p<0.01.

Table E6—: Hotel Revenues and Airbnb Entry – Heterogeneity by Hotel Tier

	Log(Price)			
	(1)	(2)	(3)	(4)
log(Incoming Air Passengers)	0.650***	0.498***	0.446***	0.425***
	(0.071)	(0.039)	(0.038)	(0.034)
log(Google Search Trend)	0.144***	0.096***	0.114***	0.113***
	(0.051)	(0.021)	(0.024)	(0.020)
log(Hotel Rooms + 1)	−0.019	−0.097	−0.195	0.049
	(0.503)	(0.155)	(0.211)	(0.346)
log(Hotel Rooms + 1)*	−0.563	−0.742***	−0.573	−0.809*
Inelastic Housing Supply	(0.541)	(0.242)	(0.405)	(0.461)
log(Airbnb Available Listings + 1)	0.090***	0.020	0.023*	0.017
	(0.029)	(0.012)	(0.012)	(0.011)
log(Airbnb Available Listings + 1)*	−0.076**	−0.063***	−0.065**	−0.072***
Inelastic Housing Supply	(0.037)	(0.023)	(0.033)	(0.023)
Hotel Tier	Luxury	Upscale	Midscale	Economy
City FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes
Observations	58,176	90,900	90,900	89,082
R^2	0.796	0.739	0.814	0.913

Note: The table shows the estimates of Equation 3 split by hotel tiers. Otherwise the table is identical to the last column in Table 4. The number of observations varies because not every geography and time period has luxury or economy hotels. Standard errors are clustered at the city level. *p<0.1; **p<0.05; ***p<0.01.

Table E7—: Hotel Revenues and Airbnb Entry – Different Measures of Airbnb

	Log(Price)			
	(1)	(2)	(3)	(4)
log(Incoming Air Passengers)	0.482***	0.466***	0.481***	0.378***
	(0.040)	(0.039)	(0.040)	(0.036)
log(Google Search Trend)	0.108***	0.110***	0.109***	0.095***
	(0.024)	(0.024)	(0.024)	(0.022)
log(Hotel Rooms + 1)	−0.094	−0.064	−0.088	−0.012
	(0.171)	(0.174)	(0.168)	(0.157)
log(Hotel Rooms + 1)* Inelastic Housing Supply	−0.604**	−0.803**	−0.660**	−0.348
	(0.282)	(0.359)	(0.287)	(0.378)
log(Active Listings + 1)	0.020**			
	(0.010)			
log(Active Listings + 1)* Inelastic Housing Supply	−0.053**			
	(0.022)			
log(Available Listings Raw + 1)		−0.001		
		(0.016)		
log(Available Listings Raw + 1)* Inelastic Housing Supply		−0.098***		
		(0.029)		
log(Available Listings + 1)			0.027**	
			(0.012)	
log(Available Listings + 1)* Inelastic Housing Supply			−0.074***	
			(0.023)	
log(Booked Listings + 1)				0.060***
				(0.009)
log(Booked Listings + 1)* Inelastic Housing Supply				0.028
				(0.018)
City FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes
Observations	90,900	90,900	90,900	90,900
R^2	0.856	0.858	0.856	0.867

Note: The table shows results of OLS estimates of Equation 3, where the size of Airbnb is measured as the number of active listings (column 1), the number of available listings unadjusted for demand-induced calendar updates (column 2), the adjusted number of available listings (column 3), and the number of booked listings (column 4). Otherwise the table is identical to Table E5.

Table E8—: Demand Own-Price Elasticities by City and Accommodation Type

	Austin	Boston	Los Angeles	Miami	New York	Oakland	Portland	San Francisco	San Jose	Seattle
Luxury	-8.35	-9.14	-9.36	-8.00	-11.03	-6.02	-5.67	-8.63	-6.13	-6.69
Upper Upscale	-5.01	-4.87	-4.42	-5.40	-7.38	-4.23	-4.54	-5.25	-5.13	-4.94
Upscale	-4.01	-4.21	-4.28	-4.51	-6.63	-3.66	-3.43	-5.04	-4.37	-4.01
Upper Midscale	-3.34	-3.85	-3.73	-4.09	-6.00	-3.46	-2.83	-5.04	-3.93	-3.42
Midscale	-2.96	-3.53	-3.24	-4.07	-6.12	-2.96	-2.58	-4.91	-3.69	-3.08
Economy	-1.66	-2.78	-2.24	-3.38	-5.45	-2.03	-1.88	-3.71	-2.69	-2.13
Airbnb Top	-4.80	-4.39	-4.45	-5.33	-5.21	-3.03	-3.36	-5.08	-3.77	-3.77
Airbnb Upper Mid	-3.98	-3.70	-3.63	-4.38	-4.34	-2.74	-3.02	-4.63	-3.29	-3.35
Airbnb Lower Mid	-3.30	-3.12	-3.02	-3.81	-3.55	-2.43	-2.52	-3.90	-2.90	-2.87
Airbnb Low	-2.52	-2.33	-2.19	-3.00	-2.56	-1.90	-2.05	-2.90	-2.12	-2.21

Note: This table displays the own-price elasticities of demand implied by our structural estimates, computed as averages at the city and accommodation type level.

Table E9—: Demand Cross-Price Elasticities by Accommodation Type

	Luxury	Upper Upscale	Upscale	Upper Midscale	Midscale	Economy	Airbnb Top	Airbnb Upper Mid	Airbnb Lower Mid	Airbnb Low
Luxury	-7.90	1.18	0.74	0.41	0.17	0.35	0.03	0.01	0.01	0.01
Upper Upscale	0.73	-5.12	0.77	0.44	0.18	0.39	0.03	0.02	0.01	0.01
Upscale	0.67	1.13	-4.42	0.45	0.19	0.41	0.03	0.02	0.01	0.01
Upper Midscale	0.63	1.12	0.77	-3.97	0.19	0.42	0.03	0.02	0.01	0.01
Midscale	0.61	1.11	0.77	0.46	-3.71	0.43	0.03	0.02	0.01	0.01
Economy	0.59	1.10	0.77	0.47	0.20	-2.79	0.03	0.02	0.01	0.01
Airbnb Top	0.68	1.16	0.78	0.47	0.20	0.44	-4.39	0.02	0.01	0.01
Airbnb Upper Mid	0.65	1.16	0.78	0.48	0.20	0.45	0.04	-3.77	0.01	0.01
Airbnb Lower Mid	0.64	1.16	0.78	0.48	0.21	0.46	0.04	0.02	-3.22	0.01
Airbnb Low	0.64	1.22	0.79	0.50	0.21	0.49	0.04	0.02	0.02	-2.45

Note: This table displays the average own and cross-price demand elasticities across the 10 room options (6 hotel tiers and 4 Airbnb quality groups) in our estimation sample, computed as averages across the cities.

Table E10—: Hotel Cost Estimates - IV versus OLS

	Hotels' Cost Function	
	(1)	(2)
$\gamma(Austin)$	13.127^{***}	3.610^{***}
	(0.429)	(0.067)
$\gamma(Boston)$	9.874^{***}	3.474^{***}
	(0.285)	(0.052)
$\gamma(LA)$	9.228^{***}	2.747^{***}
	(0.430)	(0.078)
$\gamma(Miami)$	21.587^{***}	7.915^{***}
	(0.483)	(0.104)
$\gamma(NY)$	10.399^{***}	4.618^{***}
	(0.246)	(0.055)
$\gamma(Oakland)$	7.920^{***}	2.390^{***}
	(0.421)	(0.065)
$\gamma(Portland)$	9.120^{***}	3.067^{***}
	(0.299)	(0.074)
$\gamma(SF)$	8.469^{***}	3.863^{***}
	(0.268)	(0.059)
$\gamma(SanJose)$	13.651^{***}	3.491^{***}
	(0.711)	(0.082)
$\gamma(Seattle)$	7.930^{***}	3.194^{***}
	(0.227)	(0.056)
$\gamma(UpperUpscale)$	-5.980^{***}	-1.848^{***}
	(0.233)	(0.043)
$\gamma(Upscale)$	-5.124^{***}	-1.214^{***}
	(0.282)	(0.054)
$\gamma(UpperMidscale)$	-3.457^{***}	-0.526^{***}
	(0.395)	(0.078)
$\gamma(Midscale)$	1.960^{***}	0.310^{***}
	(0.655)	(0.109)
$\gamma(Economy)$	3.210^{***}	1.670^{***}
	(0.839)	(0.161)
Regression Type	IV	OLS
Observations	54,660	54,660
R^2	0.786	0.902

Note: This table displays the coefficient estimates for $\gamma_{hn} = \gamma_h + \gamma_{m(n)}$ from Equation 10 where m denotes the city and h denotes the hotel tier. City estimates correspond to Luxury hotels. Column (1) displays IV estimates where $(q_{hn} - \nu k_{hn})$ is instrumented for with the Google Search trends, while column (2) shows OLS estimates.

Table E11—: Hotel Cost Estimates - Linear Component

Market	Luxury	Upscale	Upper Midscale	Midscale	Economy
Austin	221.53	103.82	100.71	86.93	54.16
Boston	240.04	137.65	122.03	107.44	90.31
Los Angeles	331.62	136.61	117.12	101.37	85.98
Miami	309.17	115.02	98.04	103.71	100.23
New York	371.49	179.75	155.30	136.20	143.97
Oakland	153.16	129.43	114.19	94.67	79.39
Portland	155.94	122.05	101.55	86.87	70.83
San Francisco	269.50	159.17	151.16	117.24	110.92
San Jose	178.65	121.50	128.67	117.22	93.43
Seattle	164.15	130.86	111.63	90.90	70.04

Note: This table displays the average 2014 costs of hotels across cities and tiers that are implied by our structural estimates. The costs shown here are the linear part of the hotel cost functions from Equation 6.

Table E12—: Hotel Cost Estimates - Increasing Component

Market	Luxury	Upscale	Upper Midscale	Midscale	Economy
Austin	13.13	8.00	9.67	15.09	16.34
Boston	9.87	4.75	6.42	11.83	13.08
Los Angeles	9.23	4.10	5.77	11.19	12.44
Miami	21.59	16.46	18.13	23.55	24.80
New York	10.40	5.27	6.94	12.36	13.61
Oakland	7.92	2.80	4.46	9.88	11.13
Portland	9.12	4.00	5.66	11.08	12.33
San Francisco	8.47	3.35	5.01	10.43	11.68
San Jose	13.65	8.53	10.19	15.61	16.86
Seattle	7.93	2.81	4.47	9.89	11.14

Note: This table displays the costs of hotels across cities and tiers that are implied by our structural estimates. The costs shown here are the increasing part of the hotel cost functions from Equation 6

Table E13—: Peer Hosts Cost Estimates - IV versus OLS

	Peer Hosts' Cost Function	
	(1)	(2)
$\beta(AirbnbLuxury)$	0.017***	0.007***
	(0.0004)	(0.0001)
$\beta(AirbnbUpscale)$	0.024***	0.010***
	(0.001)	(0.0002)
$\beta(AirbnbMidscale)$	0.032***	0.014***
	(0.001)	(0.0002)
$\beta(AirbnbEconomy)$	0.037***	0.023***
	(0.001)	(0.0004)
Regression Type	IV	OLS
Observations	28,801	28,801
R^2	0.416	0.689

Note: This table displays the coefficient estimates for β_a from Equation 11, where a denotes the Airbnb option. Column (1) displays IV estimates where the price is instrumented for with the Google Search trends, while column (2) shows OLS estimates.

Table E14—: Peer Hosts Mean Costs and Standard Deviation of Costs by City

	Mean Cost			
	Airbnb Economy	Airbnb Midscale	Airbnb Upscale	Airbnb Luxury
Austin	93.63	118.89	154.15	219.80
Boston	81.44	107.04	131.88	182.25
Los Angeles	85.70	110.54	135.57	184.48
Miami	100.01	129.55	165.83	232.79
New York	92.35	123.52	157.29	197.70
Oakland	71.47	93.61	110.80	146.34
Portland	69.75	84.20	100.10	129.07
San Francisco	97.48	127.99	158.49	191.27
San Jose	78.09	102.26	120.47	155.43
Seattle	76.49	95.56	118.56	158.92
Standard Deviation	26.84	30.86	41.43	58.84

Note: This table displays the mean costs for Airbnb options by city in 2014 implied by our structural estimates (Equation 11). The last line displays the estimated standard deviation of costs within each option type.

Table E15—: In and Out of Sample Model Fit

	Average Share	Avg. Deviation		Avg. Absolute Deviation	
		In Sample	Out of Sample	In Sample	Out of Sample
Overall	0.06	-0.006	-0.007*	0.019	0.022*
Luxury	0.05	-0.015	-0.014	0.031	0.037*
Upper Upscale	0.13	-0.009	-0.01	0.053	0.065*
Upscale	0.11	-0.005	0.005*	0.032	0.04*
Upper Midscale	0.08	-0.005	-0.002*	0.015	0.018*
Midscale	0.04	-0.006	-0.011*	0.01	0.014*
Economy	0.11	-0.005	-0.019*	0.022	0.029*
Airbnb Luxury	0.01	-0.002	-0.004*	0.004	0.007*
Airbnb Upscale	0.00	-0.002	-0.004*	0.003	0.005*
Airbnb Midscale	0.00	-0.002	-0.004*	0.002	0.005*
Airbnb Economy	0.00	-0.002	-0.004*	0.002	0.004*
Austin	0.07	-0.007	-0.008	0.023	0.026*
Boston	0.06	-0.005	-0.006	0.019	0.023*
Los Angeles	0.05	-0.005	-0.005	0.013	0.017*
Miami	0.05	-0.006	-0.013*	0.017	0.023*
New York	0.06	-0.005	-0.006	0.02	0.027*
Oakland	0.06	-0.006	-0.004	0.021	0.02
Portland	0.06	-0.005	-0.003*	0.015	0.017*
San Francisco	0.05	-0.006	-0.011*	0.021	0.025*
San Jose	0.06	-0.006	-0.006	0.026	0.028*
Seattle	0.06	-0.006	-0.005	0.017	0.02*

Note: This table displays the average market share across the markets and accommodation options (first column) and how well our model can replicate these market shares. To do this we simulate each market 200 times. For each simulation, we randomly draw a demand shock from the iid shocks implied by our model estimates and we compute simulated market shares for each accommodation option in a given market. We then compute the average deviation from the realized market share as well as the average absolute deviation. We do this separately for the first and second half of 2015. The first half of 2015 is considered “in sample” because it is used in the estimation, while the second half is “out of sample.” The first row implies that the average market share is 0.06, and the average deviation from the realized market share is -0.006 for the first half of 2015 and -0.007 for the second half. This means that on average we are underestimating market shares by about 10%. The average absolute deviation in sample is 0.019, while out of sample it is 0.022. This means that on average our implied market shares are off by a third approximately. The stars denote whether the difference between in sample and out of sample deviations is significant at the 5% confidence level.

Table E16—: Change in Consumer Surplus By Markets

City	Airbnb Rooms Sold (Baseline) (Thousands)	Change in CS (Million) Unconstr.	No Airbnb	Airbnb + Lodg. Tax	Airbnb + Quotas	Double Airbnb
Austin	149	-5.12	-9.65	-2.51	-3.17	4.51
Boston	210	-6.96	-14.04	-2.45	-6.17	5.78
Los Angeles	772	-26.04	-43.51	-9.14	-21.28	18.00
Miami	273	-9.41	-15.26	-3.51	-6.89	5.94
New York	1,776	-58.86	-141.25	-31.56	-79.65	61.86
Oakland	113	-3.81	-6.77	-0.93	-2.93	2.79
Portland	166	-5.67	-9.02	-0.68	-3.89	3.93
San Francisco	635	-21.51	-47.64	-10.83	-25.89	20.08
San Jose	115	-3.88	-6.51	-0.96	-3.30	2.85
Seattle	175	-5.98	-11.03	-2.24	-3.96	4.69
All	4,381	-147.23	-304.70	-64.79	-157.12	130.43
Non-Compression	3,218	-107.99	-183.26	-41.09	-143.38	76.95
Compression	1,163	-39.24	-121.44	-23.70	-13.74	53.48

Note: This table displays the change in consumer surplus from five alternative scenarios, two scenarios without Airbnb and three scenarios with Airbnb and regulation. The table splits the consumer surplus results of Table 6 by city and compression nights.

Table E17—: Competitive Effects on Hotels By Markets

City			Rooms Sold (MM)						Revenues ($MM)			
	Basel.	Unconstr.	No Airbnb	Lodg. Tax	Quotas	Double Airbnb	Basel.	Unconstr.	No Airbnb	Lodg. Tax	Quotas	Double Airbnb
Austin	8	8	8	8	8	8	1,043	1,059	1,056	1,046	1,050	1,038
Boston	14	14	14	14	14	14	2,477	2,502	2,495	2,480	2,489	2,469
Los Angeles	28	29	29	28	29	28	4,162	4,239	4,227	4,176	4,207	4,136
Miami	14	14	14	14	14	14	2,643	2,678	2,673	2,649	2,664	2,631
New York	33	34	33	33	33	32	8,830	9,148	9,037	8,871	8,979	8,750
Oakland	5	6	6	5	6	5	635	644	643	636	640	632
Portland	7	7	7	7	7	7	795	808	807	796	802	790
San Francisco	16	16	16	16	16	16	3,259	3,347	3,318	3,272	3,301	3,234
San Jose	10	10	10	10	10	10	1,410	1,421	1,419	1,411	1,416	1,406
Seattle	11	11	11	11	11	11	1,550	1,567	1,563	1,552	1,557	1,544
All	146	149	148	146	147	145	26,803	27,412	27,238	26,891	27,106	26,630
Non Compression	113	116	115	114	115	113	19,563	19,977	19,898	19,633	19,850	19,431
Compression	33	33	33	33	33	32	7,240	7,435	7,341	7,258	7,256	7,199

City			Profits ($MM)						Alternative Profits ($MM)			
	Basel.	Unconstr.	No Airbnb	Lodg. Tax	Quotas	Double Airbnb	Basel.	Unconstr.	No Airbnb	Lodg. Tax	Quotas	Double Airbnb
Austin	289	295	294	290	289	287	594	604	603	596	598	591
Boston	580	587	587	581	582	577	1,345	1,359	1,356	1,347	1,351	1,340
Los Angeles	510	520	527	513	513	503	2,154	2,194	2,193	2,162	2,177	2,139
Miami	543	552	550	544	543	540	1,823	1,847	1,845	1,827	1,837	1,813
New York	2,264	2,350	2,354	2,281	2,310	2,230	5,440	5,633	5,591	5,470	5,540	5,380
Oakland	89	91	92	90	90	88	149	152	153	150	151	148
Portland	125	127	128	125	125	123	313	318	318	313	315	310
San Francisco	615	633	640	621	627	605	1,705	1,751	1,744	1,714	1,730	1,689
San Jose	390	393	393	390	391	389	594	598	599	595	597	592
Seattle	282	286	287	283	283	280	752	761	760	754	756	749
All	5,687	5,833	5,852	5,718	5,754	5,623	14,869	15,216	15,162	14,928	15,050	14,750
Non Compression	2,272	2,327	2,357	2,289	2,330	2,243	10,454	10,682	10,661	10,498	10,624	10,373
Compression	3,414	3,505	3,495	3,429	3,424	3,380	4,414	4,535	4,501	4,430	4,426	4,377

Note: This table displays hotel bookings, revenue, and profits from the baseline and five alternative scenarios, two scenarios without Airbnb and three scenarios with Airbnb and regulation. The table splits the hotel results of Table 6 by city and compression nights. The costs used in the profit calculation are those estimated from Equation 6, except that we exclude the increasing cost component from the computed costs. The costs used in the alternative profit calculation are derived from imputed accounting costs combining the wage bill in the STR data and trends in the wages of maids. This is likely a lower bound on the true marginal cost of hotels.

Table E18—: Peer Producer Surplus

City	Rooms Sold (Thousands)				Revenues ($Thousands)				Total Peer Surplus ($Thousands)			
	Basel.	Lodg. Tax	Quotas	Double Airbnb	Basel.	Lodg. Tax	Quotas	Double Airbnb	Basel.	Lodg. Tax	Quotas	Double Airbnb
Austin	149	111	64	206	20,576	13,916	10,819	26,936	3,604	2,420	1,765	4,604
Boston	210	167	77	296	22,053	16,298	8,270	28,494	5,121	3,812	1,936	6,675
Los Angeles	772	606	251	1,088	82,794	60,009	26,929	106,710	19,413	14,212	6,671	25,424
Miami	273	211	90	378	35,076	25,254	12,875	45,475	6,135	4,386	2,217	7,842
New York	1,776	1,400	585	2,498	225,359	164,190	76,004	294,644	46,722	33,895	16,359	60,979
Oakland	113	96	41	159	8,792	6,957	3,160	10,838	2,769	2,242	1,019	3,590
Portland	166	151	62	240	13,435	11,778	5,066	17,101	4,411	3,896	1,725	5,831
San Francisco	635	492	210	900	81,221	58,480	27,714	106,600	16,567	11,858	5,869	21,718
San Jose	115	94	34	162	10,736	8,172	3,291	13,634	2,830	2,193	845	3,704
Seattle	175	139	75	250	16,537	12,074	7,320	21,168	4,477	3,307	2,071	5,840
All	4,381	3,468	1,491	6,177	516,577	377,128	181,446	671,600	112,048	82,220	40,477	146,206
Non Compression	3,218	2,527	482	4,528	371,852	270,032	55,957	482,062	80,602	58,941	12,860	105,188
Compression	1,163	942	1,009	1,649	144,725	107,096	125,489	189,538	31,446	23,280	27,617	41,018

Note: This table displays Airbnb bookings, revenue, and profits from the baseline and three alternative scenarios, two scenarios without Airbnb and three scenarios with Airbnb and regulation. The table splits the Airbnb results of Table 6 by city and compression nights. Airbnb costs are taken from the distribution by the parameter estimates of Equation 7 truncated at zero (i.e., negative costs are considered equal to zero).

Table E19—: Airbnb Bookings: Market Expansion versus Business Stealing

City	Share New Bookings	
	Unconstrained	No Airbnb
Austin	0.29	0.49
Boston	0.33	0.60
Los Angeles	0.32	0.51
Miami	0.33	0.51
New York	0.33	0.70
Oakland	0.32	0.55
Portland	0.32	0.49
San Francisco	0.33	0.69
San Jose	0.33	0.51
Seattle	0.33	0.57
All	0.33	0.62
Non-Compression Nights	0.33	0.53
Compression Nights	0.31	0.87

Note: This table shows the share of Airbnb bookings in the *'Baseline'* scenario that would not have been hotel bookings in the two counterfactual scenarios without Airbnb. This represents the share of Airbnb bookings constituting market expansion. The two counterfactual scenarios are defined as in Table 6. All calculations are for 2014.

Table E20—: Aggregate Surplus (MM) – Standard Logit Estimates

	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	26,804	4,847	4.38	517	112	3,986
No Airbnb (Unconstrained)	-175	148	27,306	4,959				4,055
No Airbnb	-274	147	27,117	4,954				4,027
Airbnb With Lodging Tax	-55	146	26,863	4,866	3.53	385	84	4,055
Airbnb With Quotas	-153	147	27,026	4,890	1.49	181	40	4,015
Double Airbnb Rooms	107	146	26,689	4,809	6.01	649	141	3,971
Panel B: Compression Nights in 2014 (19.6% of all markets)								
Baseline		33	7,241	2,871	1.16	145	31	1,084
No Airbnb (Unconstrained)	-47	33	7,410	2,942				1,108
No Airbnb	-98	33	7,310	2,923				1,093
Airbnb With Lodging Tax	-19	33	7,251	2,880	0.95	108	24	1,103
Airbnb With Quotas	-12	33	7,252	2,878	1.01	125	28	1,086
Double Airbnb Rooms	39	33	7,215	2,851	1.61	184	40	1,081

Note: This table is the same as Table 6 except that it uses the demand and supply estimates without consumer preference heterogeneity. The demand parameter estimates used for this counterfactual scenarios are presented in the last two columns of Table 5. All variables are in millions.