APPENDIX

The Welfare Effects of Peer Entry in the Accommodation Market: The Case of Airbnb

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A Appendix: Proof of Model Predictions

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

We are left with proving that hotel rooms sold decrease in K_a if and only if $-\frac{\partial Q_h}{\partial p_a} / \frac{\partial Q_h}{\partial p_h} \geq -\frac{\partial^2 \Pi_h}{\partial p_h \partial p_a} / \frac{\partial^2 \Pi_h}{\partial p_h^2}$. In words, this condition requires that the hotel best response function to competitor prices is steeper when hotel occupancy is held fixed than when hotel occupancy is allowed to change.[20] The total derivative of hotel rooms sold with respect to Airbnb capacity is equal to

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

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

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

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

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

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

The next proposition contains comparative statics results on the long-run entry of peer supply. We define the expected daily benefit of joining Airbnb as $v_a = \int_d E_c \left(max\{0, p_a^d - c\}\right) dF(d)$, and the one-time cost of joining as C, randomly drawn for each potential host. We also let T denote 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 $C \leq Tv_a$.

Proposition 3 *Entry of flexible sellers is larger (K_a increases) if the distribution of peers' marginal costs c decreases in the sense of first-order stochastic dominance. K_a increases if K_h decreases. K_a also increases if $F(d)$ increases in the sense of first order stochastic dominance or in response to a mean-preserving spread in $F(d)$.*

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

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

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

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

B Appendix: Endogeneity Concerns

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

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

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

Table A1: Hotel Revenue and Airbnb - Additional Controls

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

Note: Standard Errors Clustered at a City Level

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

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

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

Note: Standard Errors Clustered at a City Level

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

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

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

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

C Appendix: Additional Details and Results from the Structural Estimation

C.1 Formulation of Differentiation Instruments

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

- $IV_{1jn} = \sum_{i \neq j} \mathbb{1}\left(abs(\hat{\hat{p}}_{in} - \hat{\hat{p}}_{jn}) < std_{\hat{p}_c}\right)$, where $std_{\hat{p}_c}$ is the standard deviation of predicted prices over time within city c.

- $IV_{2jn} = \sum_{i=j-1} \hat{\hat{p}}_{in} - \hat{\hat{p}}_{jn}$. This is equal to zero for luxury hotels, and the highest quality Airbnb tier.

- $IV_{3jn} = \sum_{i=j-1} (\hat{\hat{p}}_{in} - \hat{\hat{p}}_{jn})^2$. This is equal to zero for luxury hotels, and the highest quality Airbnb tier.

- $IV_{4jn} = \sum_{i=j+1} \hat{\hat{p}}_{in} - \hat{\hat{p}}_{jn}$. This is equal to zero for economy hotels, and the lowest quality Airbnb tier.

- $IV_{5jn} = \sum_{i=j+1} (\hat{\hat{p}}_{in} - \hat{\hat{p}}_{jn})^2$. This is equal to zero for economy hotels, and the lowest quality Airbnb tier.

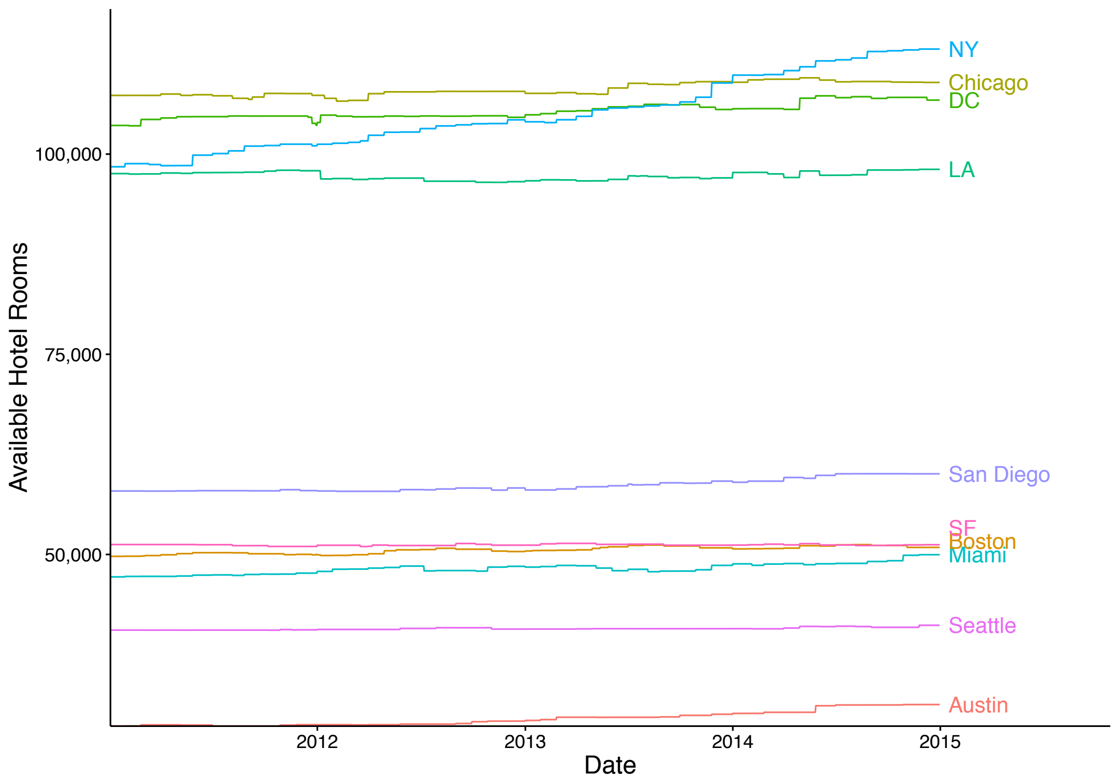
- $IV_{6jn} = \sum_{i \in \text{hotels}} \left(\hat{\hat{p}}_{in} - \hat{\hat{p}}_{jn}\right)$. This is equal to zero for Airbnb options.

- $IV_{7jn} = \sum_{i \in \text{hotels}} (\hat{\hat{p}}_{in} - \hat{\hat{p}}_{jn})^2$. This is equal to zero for Airbnb options.

We then do a principal component decomposition of IV, and keep the largest factors accounting for 75% of the variation.

C.2 Additional Figures and Tables

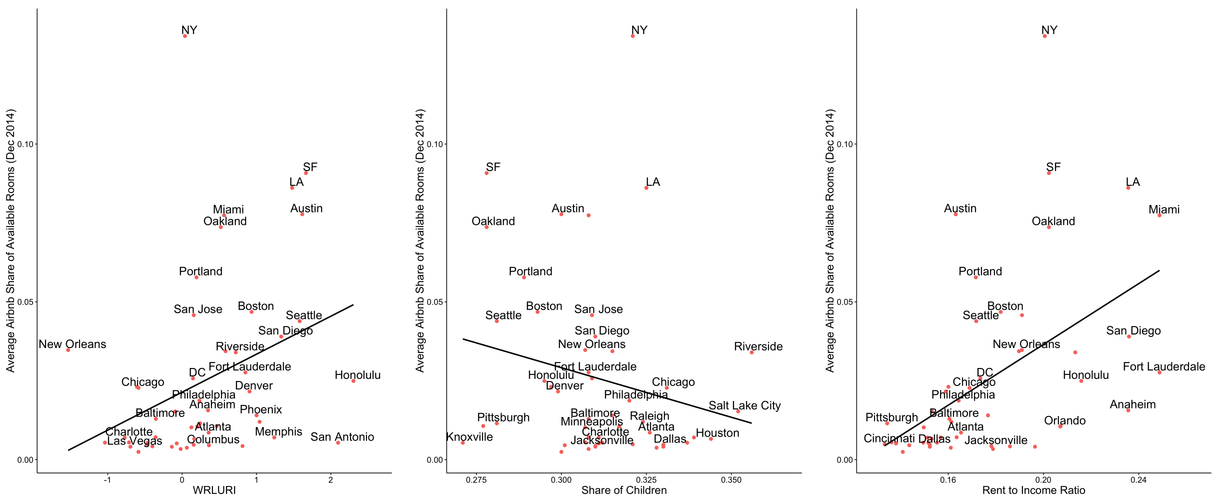
Figure A1: Hotel Rooms



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

Figure A2: Peer Production and Supply Characteristics

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



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

Table A4: Heterogeneous Effects of Airbnb: Hotel Scale

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

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

Table A5: Demand Own-Price Elasticities by City and Accommodation Type

	Austin	Boston	Los Angeles	Miami	New York	Oakland	Portland	San Francisco	San Jose	Seattle
Luxury	-7.49	-8.30	-6.87	-5.16	-8.54	-5.28	-4.84	-7.53	-5.19	-5.89
Upper Upscale	-1.22	-1.35	-1.48	-3.04	-3.37	-1.27	-1.74	-2.21	-1.98	-1.85
Upscale	-3.72	-3.59	-3.92	-3.98	-5.75	-3.42	-3.21	-4.43	-3.92	-3.69
Upper Midscale	-3.24	-3.63	-3.64	-3.73	-5.77	-3.44	-2.81	-4.59	-3.75	-3.29
Midscale	-2.97	-3.53	-3.25	-3.83	-6.24	-3.05	-2.65	-4.83	-3.68	-3.14
Economy	-1.59	-2.72	-1.99	-3.08	-5.34	-1.94	-1.88	-3.29	-2.50	-2.09
Airbnb Top	-4.89	-4.53	-4.57	-5.46	-5.49	-3.20	-3.42	-5.02	-3.86	-3.89
Airbnb Upper Mid	-4.15	-3.87	-3.82	-4.55	-4.75	-2.91	-3.09	-4.69	-3.44	-3.51
Airbnb Lower Mid	-3.56	-3.35	-3.29	-4.08	-3.96	-2.66	-2.63	-4.05	-3.10	-3.07
Airbnb Low	-2.79	-2.50	-2.44	-3.27	-2.93	-2.11	-2.14	-3.11	-2.36	-2.42

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 A6: 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	-6.91	4.32	0.04	0.02	0.01	0.02	0.00	0.00	0.00	0.00
Upper Upscale	2.44	-2.02	0.03	0.02	0.01	0.02	0.00	0.00	0.00	0.00
Upscale	0.03	0.04	-4.24	0.78	0.31	0.67	0.04	0.02	0.01	0.01
Upper Midscale	0.03	0.04	1.32	-3.99	0.32	0.69	0.04	0.02	0.01	0.01
Midscale	0.03	0.04	1.29	0.76	-3.85	0.70	0.04	0.02	0.01	0.01
Economy	0.03	0.05	1.24	0.75	0.32	-2.70	0.04	0.02	0.02	0.01
Airbnb Top	0.04	0.05	1.32	0.79	0.33	0.74	-4.77	0.03	0.02	0.01
Airbnb Upper Mid	0.03	0.05	1.28	0.79	0.33	0.75	0.06	-4.09	0.02	0.01
Airbnb Lower Mid	0.03	0.05	1.24	0.78	0.33	0.76	0.06	0.03	-3.53	0.01
Airbnb Low	0.03	0.05	1.21	0.78	0.33	0.81	0.06	0.04	0.03	-2.66

This table displays the average own and cross-price demand elasticities across the 10 hotel scales in our estimation sample, computed as averages across the cities.

Table A7: Hotel Cost Estimates - Linear Component

STR_name	Luxury	Upper Upscale	Upscale	Upper Midscale	Midscale	Economy
Austin/TX	201.986	80.726	68.202	67.162	53.633	20.935
Boston/MA	213.879	132.860	103.347	87.744	71.723	54.383
Los Angeles/Long Beach/CA	297.744	116.987	106.164	85.632	68.541	52.963
Miami/Hialeah/FL	258.789	115.807	77.140	61.519	67.784	62.662
New York/NY	324.235	170.181	138.283	111.068	94.698	96.956
Oakland/CA	122.613	97.103	97.839	78.801	59.553	43.948
Portland/OR	118.310	106.172	85.069	62.775	48.416	31.632
San Francisco/San Mateo/CA	200.413	126.514	91.844	87.878	60.522	51.452
San Jose/Santa Cruz/CA	137.933	115.922	98.412	86.231	69.545	50.333
Seattle/WA	141.331	134.288	104.541	84.645	64.181	42.936

This table displays the coefficient estimates for the linear part of the hotel cost functions from Equation 7.

Table A8: Hotel Cost Estimates - Increasing Component

STR_name	Luxury	Upper Upscale	Upscale	Upper Midscale	Midscale	Economy
Austin/TX	12.294	7.341	7.889	8.680	12.075	12.726
Boston/MA	7.918	2.966	3.513	4.305	7.700	8.351
Los Angeles/Long Beach/CA	6.917	1.964	2.512	3.303	6.698	7.349
Miami/Hialeah/FL	21.719	16.766	17.314	18.106	21.500	22.151
New York/NY	8.249	3.296	3.844	4.635	8.030	8.681
Oakland/CA	5.599	0.646	1.194	1.986	5.380	6.032
Portland/OR	6.600	1.648	2.195	2.987	6.382	7.033
San Francisco/San Mateo/CA	7.076	2.123	2.671	3.462	6.857	7.508
San Jose/Santa Cruz/CA	7.565	2.612	3.159	3.951	7.346	7.997
Seattle/WA	6.300	1.347	1.895	2.687	6.081	6.732

This table displays the coefficient estimates for the increasing part of the hotel cost functions from Equation 7.

Table A9: Airbnb Mean Costs and Standard Deviation of Costs by City

	Mean Cost			
	Airbnb Economy	Airbnb Midscale	Airbnb Upscale	Airbnb Luxury
Austin	90.85	122.14	159.62	218.77
Boston	76.58	107.16	131.56	179.22
Los Angeles	83.05	114.52	138.41	184.96
Miami	100.78	134.33	170.73	233.39
New York	90.77	127.41	161.58	195.48
Oakland	69.23	94.66	110.99	144.80
Portland	64.70	82.18	98.60	127.53
San Francisco	94.20	129.34	159.46	186.56
San Jose	75.43	101.58	120.36	152.46
Seattle	72.56	93.56	118.10	156.38
Standard Deviation	21.52	31.48	43.94	59.82

This table displays the mean costs for Airbnb options by city in 2014. The last line displays the estimated standard deviation of costs within each option type. The costs are obtained from a 2SLS regression where the normal inverse of the share of active listings booked is regressed on price, city-specific trends, year-month fixed effects, and city by day-of-week fixed effects. This is simply a transformation of Equation 8, as described in Section 4.1. The instruments for price are log Google searches for hotels and log number of passengers traveled. The regressions are run separately by each hotel scale and achieve r-squared values ranging between .34 and .46.

Table A10: Competitive Effects on Hotels

City	Quantity (000's)		Revenue (MM)		Profit (MM)		Alt. Profit (MM)	
	Base	Price Adj.	Base	Price Adj.	Base	Price Adj.	Base	Price Adj.
Austin	8241	8320	1043	1056	289	295	594	602
Boston	14025	14122	2477	2495	451	458	1345	1355
Los Angeles	28199	28608	4162	4218	333	349	2154	2182
Miami	14062	14198	2642	2668	555	566	1822	1840
New York	32526	33176	8830	9029	1665	1748	5440	5570
Oakland	5452	5514	635	644	51	54	149	153
Portland	6907	7006	795	807	78	82	313	318
San Francisco	15714	15958	3258	3313	501	522	1705	1735
San Jose	9525	9585	1410	1420	158	161	594	599
Seattle	11294	11384	1550	1564	201	206	752	760
All	145946	147871	26802	27214	4282	4440	14868	15115
All (Compression)	32552	32875	7239	7364	2505	2585	4414	4509
All (Non Compression)	113394	114996	19563	19849	1777	1855	10454	10606

This table displays hotel bookings, revenue, and profits with and without Airbnb. All calculations are for 2014. "Base" refers to the current scenario with Airbnb, "Price Adj." refers to the counterfactual scenario in which hotels adjust prices in response to the absence of Airbnb. Row "All" refers to the sum across all cities, and "All (Compression)" refers to the sum across cities for time periods when at least one hotel option in the city has an occupancy of at least 95%. The costs used in the first profit calculation are those estimated from equation 7, except that we exclude the increasing cost component from the computed costs. The costs used in the second 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.