Airbnb, Hotels, and Localized Competition

EEA ESEM 2022

Maximilian Schaefer
Yale University

Kevin Ducbao Tran
University of Bristol

August 24, 2022

Motivation

- $\rightarrow$ Entry of peer-to-peer marketplaces:
  - $+$ Benefits consumers through increased variety and lower prices
  - $-$ Lowers prices to the detriment of established industries
- $\rightarrow$ A reallocation of total welfare to the detriment of established (and more heavily regulated) industries?

This paper

→ Quantify total welfare effect of Airbnb's entry into hospitality industry:

  * Estimate structural model of demand and calibrate supply-side
  * Counterfactual simulations: gains/losses from removing Airbnb

→ Novelty:

  * Accounting for the geographic dimension of competition
    → Nearby units are closer substitutes
    → Welfare calculations by district

Related literature

Competition established industries vs. sharing economy:

* Seamans and Zhu [2014], Kroft and Pope [2014], and Cramer and Krueger [2016]

Consumer surplus from sharing economy:

* Cohen, Hahn, Hall, Levitt, and Metcalfe [2016] and Lam, Liu, and Hui [2021]

Competition Airbnb vs. hotels:

* Zervas, Proserpio, and Byers [2017]

Impact of Airbnb on total welfare:

* Farronato and Fradkin [2022]

Data

→ Sample: Paris, 2017

→ Daily accommodation-level data from three different sources:

- ∗ Hotel occupancy data (INSEE)
- ∗ Hotel price data [Hunold, Kesler, and Laitenberger, 2020]
- ∗ Airbnb occupancy & price data (Airdna)

Data Aggregation

→ We aggregate the data to define products as **Location–Type–Quality** combination:

Location: Districts of Paris ▸ Map

Type: Hotel or Airbnb

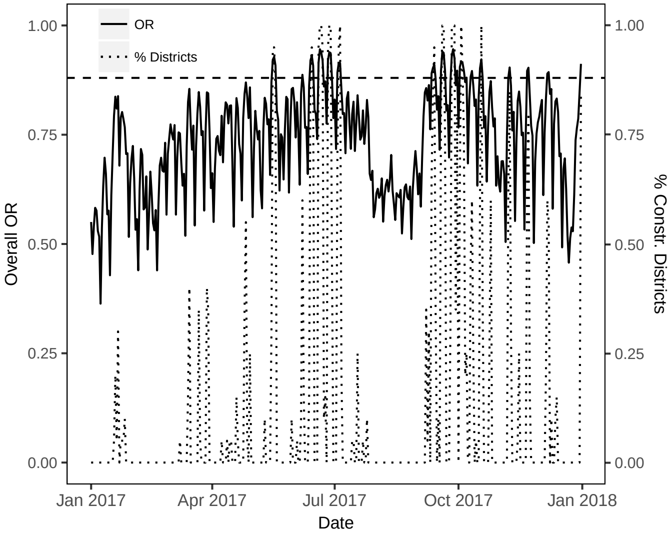
Hotel Quality: 1 to 5 stars (official)
Airbnb Quality: 1 to 4 "stars" (fixed effects)

Examples: 5 star hotel in district 1, 4 'star' Airbnb in district 2, etc...

→ While quantity information is complete, we cannot match all hotel price data and have to drop certain days from the sample ▸ matched vs. non-matched hotels

→ ▸ Summary statistics ▸ Flexible supply vs flexible prices

Location-Specific Demand Shocks



→ OR : Occupancy Ratio = # occupied/ # available

→ % constr. districts
% districts with OR > 0.9

→ ‣ Prices and occupancy

Demand – Three-Level Nested Logit [Verboven, 1996]

Sequential choice model

$$ln(s_{jt}/s_{0t}) = x_{jt}\beta - \alpha p_{jt} + (\sigma_2 - \sigma_1) ln(s_{jt}/s_{hdt}) + \sigma_2 ln(s_{jt}/s_{dt}) + \epsilon_{jt} \quad (1)$$

- → s_{jt}: share of product j at date t
- → s_{hdt}: share of type h in district d
- → $s_{dt} = \sum_h s_{hdt}$ (share in district d)
- → s_{0t}: share of outside good Market size
- → $0 \leq \sigma_2 \leq \sigma_1 \leq 1$
- → x_{jt} contains constant, quality-type fixed effects, sometimes time fixed effects, capacities

Identification challenges:

- → location-specific demand shocks → instruments Instruments
- → underlying capacities → account for capacity Accounting for capacities

Demand Estimates

▸ First-stage F-statistics ▸ Full results ▸ Elasticities

	(1)	(2)	(3)	(4)	(5)
	Logit	Logit (IV)	NL	NL	NL
Price (α)	0.002^{***}	-0.008^{***}	-0.006^{***}	-0.006^{***}	-0.005^{***}
	(0.0001)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
σ_1			0.758^{***}	0.657^{***}	0.717^{***}
			(0.017)	(0.014)	(0.018)
σ_2			0.256^{***}	0.228^{***}	0.207^{***}
			(0.010)	(0.009)	(0.006)
Market FE	N	N	N	Y	Y
Capacities	N	N	N	N	Y
N	33,504	33,504	33,504	33,504	33,504
Adjusted R^2	0.377	0.133	0.652	0.700	0.862

→ Quality-Type FEs always included

→ 4 "star" Airbnb ≈ 2 star hotels

→ ***: one percent significance

Counterfactual: Outline

- → Goal: Estimate consumer welfare and hotel revenues with and without Airbnb
- → Airbnb benefits consumers
    1. More choices
    2. Competition → lower prices
- → Following Farronato and Fradkin [2022]:
    - ∗ ΔCS w/o hotel-price adjustments = Δ from reduced variety
    - ∗ ΔCS w/ hotel-price adjustments = Δ (reduced variety + higher hotel prices)
    - ∗ ΔCS w/ - ΔCS w/o = Δ from higher hotel prices

Main Challenges

→ Demand vector needs to fulfill capacity constraints of hotels

→ Hotel pricing is non-linear, and depends on rival capacity → hard to solve analytically

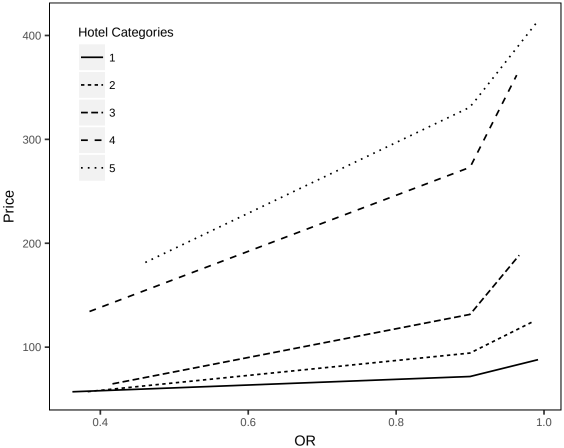
→ Proposition: Numerical equilibrium simulation

Market Clearing with Capacity Constraints – Inner Loop

→ Given price vector $\boldsymbol{p}$ and choice set $\boldsymbol{J}$

1. Calculate the demand, $q_j(\boldsymbol{p})$, $\forall j \in \boldsymbol{J}$
2. Calculate $\mathcal{E} = \sum_{j \in \boldsymbol{J^c}} (q_j(\boldsymbol{p}) - c_j)$
   where $\boldsymbol{J^c}$ denotes the set of hotels for which $q_j(\boldsymbol{p}) > c_j$
3. If $\mathcal{E} > 0$, repeat 1. and 2. using $\mathcal{E}$ as "residual" market size and $\boldsymbol{J} \setminus \boldsymbol{J^c}$ as choice set
   If $\mathcal{E} = 0$, stop.

Hotel Prices



Estimated hotel pricing functions for selected district

Hotel Prices – Outer Loop

→ Estimate $p_j(q) \quad \forall j$

→ Initiate $\mathbf{p}^\kappa$

1. Calculate $\mathbf{q}^\kappa = \mathbf{q}(\mathbf{p}^\kappa)$, as described previously
2. Calculate $p_j(q_j^\kappa)$
   If $\exists j : p_j(q_j^\kappa) \neq p_j^\kappa$, set $p_j^{\kappa+1} = p_j(q_j^\kappa)$, go back to (1) for $\kappa + 1$
3. Stop if $p_j(q_j^\kappa) = p_j^\kappa \quad \forall j$

→ ‣ Observed vs. simulated

Consumer Surplus and Hotel Revenues

- → Average gain in consumer surplus per consumer and night
  - ∗ Taking into account hotel price adjustment: 31 euro
  - ∗ Ignoring hotel price adjustment: 23 euro
  - → Price effect ≈ 26 percent ▸ Heterogeneity
- → Multiplied by market size per night
  - ∗ Taking into account hotel price adjustment: 4.2 million euro
  - ∗ Ignoring hotel price adjustment: 3.1 million euro
- → Hotel revenues
  - ∗ Average aggregate daily revenue change: 1.9 million euro ▸ Details

Airbnb Demand

→ Minority of Airbnb consumers switch to hotels

- With price adjustment: 28 percent
- Without price adjustment: 48 percent

Conclusion

→ Consumer surplus from Airbnb amounts to 31 Euro by traveller and night.

- ∗ Average of 4.2 million euro per night
- ∗ $\approx$ 26 percent due to price effect ($p \downarrow$)
- ∗ Pronounced in periods of high demand
- ∗ District heterogeneity in total effect and relative price effect

→ On average hotels incur revenue losses of 1.9M ($\approx 21\%$) euro by night.

→ Share of Airbnb bookings that constitute market expansion: 72 percent

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Matched vs Non-Matched Hotels ◂ Back

Star Rating	Share	Rooms Occupied		Rooms Offered	
		Matched	Non-matched	Matched	Non-matched
1	19.25	907.73	205.50	1278.78	304.71
		(153.63)	(34.94)	(8.94)	(9.13)
2	27.79	4753.02	1859.66	6423.65	2472.21
		(895.84)	(350.75)	(49.79)	(46.05)
3	35.84	15900.61	8877.17	20370.08	11378.27
		(2579.40)	(1397.01)	(58.68)	(131.76)
4	40.25	11686.96	8061.20	15236.77	10265.54
		(1881.30)	(1305.69)	(522.86)	(387.19)
5	35.48	2934.05	1650.19	4182.78	2300.53
		(488.89)	(321.76)	(60.70)	(171.71)

Notes: Room capacities and occupation by hotel categories.

Summary Statistics ◂ Back

Quality	Price		Rooms Occupied		Rooms Offered	
	Hotels	Airbnb	Hotels	Airbnb	Hotels	Airbnb
1	81.33	41.43	1112.61	4214.60	1583.48	12577.39
	(15.73)	(1.60)	(186.98)	(847.23)	(11.37)	(1267.82)
2	99.63	64.03	6599.36	4258.33	8895.86	12885.61
	(17.00)	(1.94)	(1228.55)	(849.14)	(86.78)	(1304.51)
3	125.93	92.67	24714.45	4550.64	31748.35	14160.72
	(23.02)	(2.92)	(3906.06)	(964.24)	(131.52)	(1291.13)
4	192.81	172.83	19708.64	4539.22	25502.31	15036.03
	(31.89)	(8.07)	(3093.73)	(1138.67)	(388.45)	(1118.71)
5	485.10	-	4579.63	-	6483.31	-
	(79.59)	-	(796.29)	-	(225.32)	-

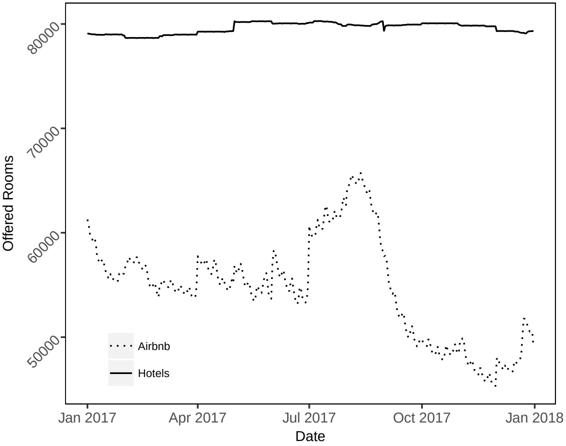
Notes: Simple averages. Standard deviations in parentheses.

Spatial Distribution ◂ Back I ◂ Back II

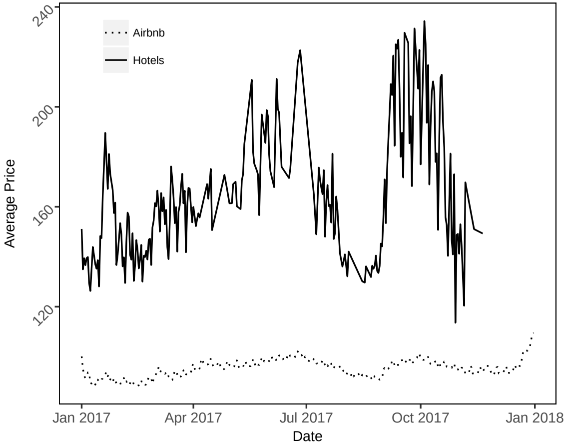
Airbnb

Hotels

Flexible Supply vs. Flexible Prices ▸ Occupancy ◂ Back

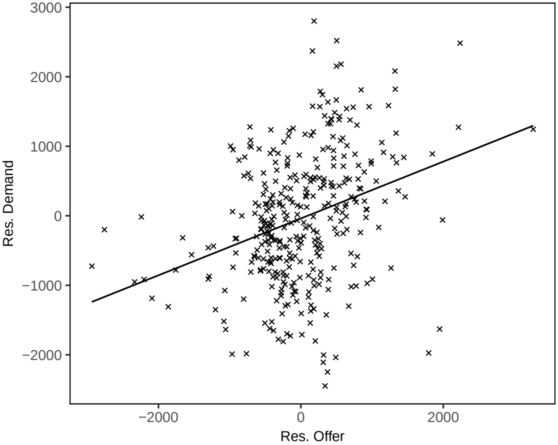


Rooms Offered

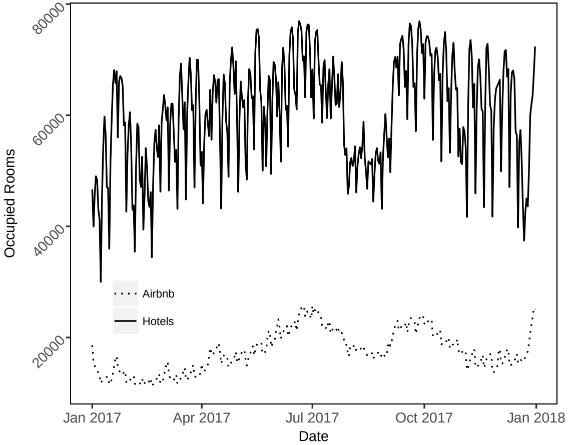


Airbnb and Hotel Prices over Time

Occupancy ◂ Back

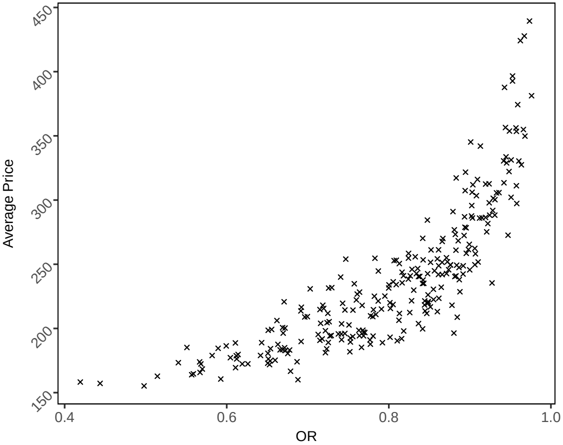


Deseasonalized Airbnb Occupancy vs. Airbnb Offer

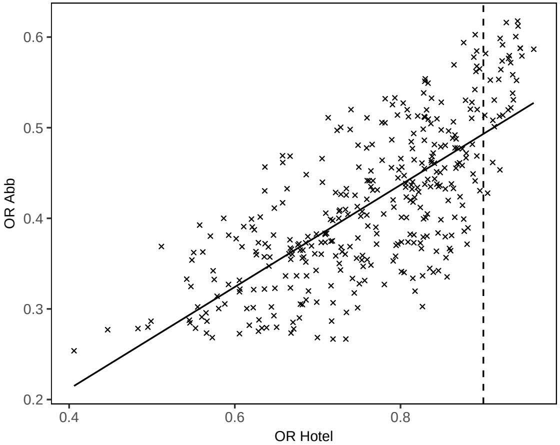


Occupancy

Zooming into a Selected District ◂ Back

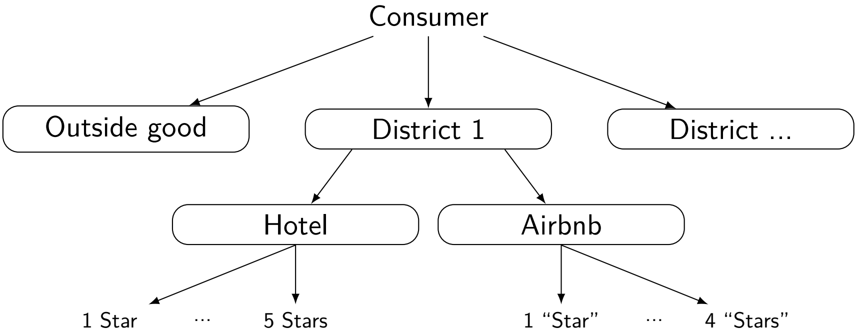


Hotel Prices and Occupancy



OR Airbnb vs hotels

Demand Model – Three-Level Nested Logit ◂ Back



Market Size ◂ Back

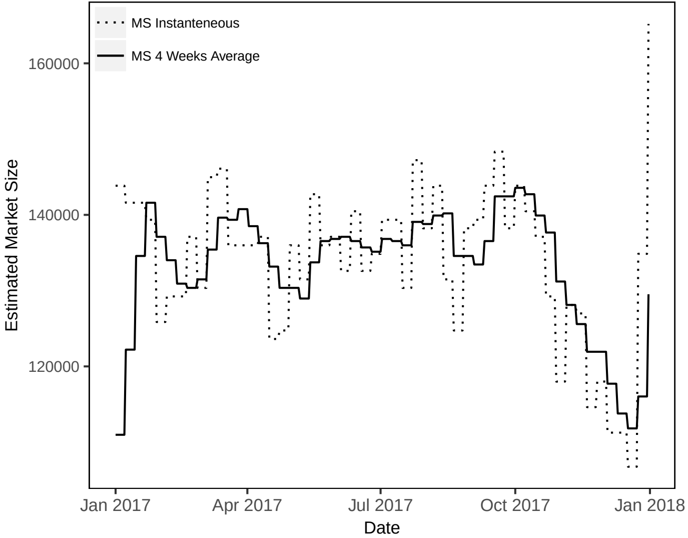
→ Market size: Number of people looking for a short-term accommodation in Paris

→ We use *global* Google Trends data:

1. Sum of trends for the keywords "hotels Paris" and "Airbnb Paris"
2. Set scale: mean value of trend = mean number of rooms offered in 2017

   Intuition: Capacity adjusts to demand in the long-run ▸ plot

Market Size ◂ Back



Instrumental Variables ◂ Back

→ Make use of competitors' room capacities and geographic distance between districts

$$z_{jt} = \sum_{\substack{l \in A_j \\ l \neq j}} \frac{c_{lt}}{e_{lj}^2}, \tag{2}$$

→ c_{lt}: capacity, e_{lt}: distance ▸ predicted Airbnb offer

→ We create IVs using different A_j:

* Competitors of same type and quality in other districts
* Competitors of different type and same quality in other districts
* Competitors of different type and same quality in same district
* Competitors of different type in the same district

→ Interact all IVs with the market size (z_{jt}/MS) and a dummy variable for hotels

Accounting for Capacities ◂ Back

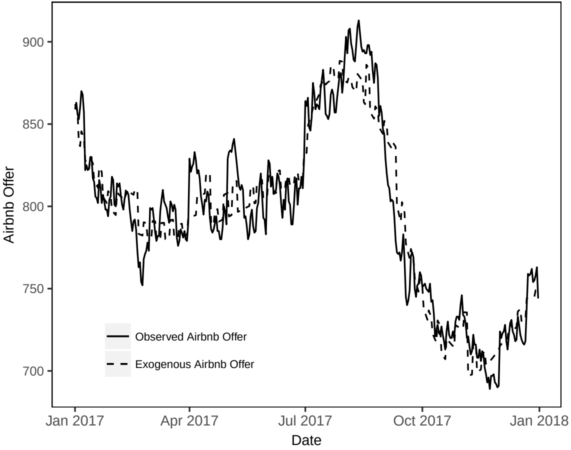
- $\rightarrow$ Observed shares are driven by underlying capacities
- $\rightarrow$ high-capacity $\rightarrow$ high share ▸ Spatial Distribution
- $\rightarrow$ Hotels:
  - $*$ Fixed effect for districts with > 2000 four- and five-star hotel rooms
- $\rightarrow$ Airbnb:
  - $*$ Include log of predicted exogenous Airbnb capacity [as in Ackerberg and Rysman, 2005]

Predicting Airbnb Capacities using Traffic Data ◂ Back I

→ Predict Airbnb supply using

- ∗ Quartic time trend
- ∗ Outgoing leisure car traffic at main highway exits around Paris
  - ▸ Each day before weekend/holiday: Outgoing traffic minus average outgoing traffic in preceding week

Predicting Airbnb Capacities using Traffic Data ◂ Back II



Predicted vs. Observed Airbnb Offer

Full demand estimates ◂ Back I

Table 1: Parameter estimates

	(1) Logit	(2) Logit (IV)	(3) NL	(4) NL	(5) NL
Price	0.002^{***}	-0.008^{***}	-0.006^{***}	-0.006^{***}	-0.005^{***}
	(0.0001)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
σ_1			0.758^{***}	0.657^{***}	0.717^{***}
			(0.017)	(0.014)	(0.018)
σ_2			0.256^{***}	0.228^{***}	0.207^{***}
			(0.010)	(0.009)	(0.006)
Airbnb category 2	0.290^{***}	0.501^{***}	0.068^{***}	0.132^{***}	-0.019^{*}

Full demand estimates ◂ Back II

	(0.041)	(0.044)	(0.021)	(0.023)	(0.011)
Airbnb category 3	0.421***	0.924***	0.280***	0.379***	0.078***
	(0.040)	(0.047)	(0.027)	(0.027)	(0.018)
Airbnb category 4	0.261***	1.586***	0.774***	0.920***	0.456***
	(0.042)	(0.067)	(0.044)	(0.044)	(0.038)
1-star hotel	−0.539***	−0.148***	0.698***	0.619***	2.553***
	(0.048)	(0.052)	(0.034)	(0.030)	(0.066)
2-star hotel	0.740***	1.319***	0.968***	1.032***	2.712***
	(0.041)	(0.048)	(0.025)	(0.025)	(0.093)
3-star hotel	2.067***	2.922***	1.463***	1.674***	3.232***
	(0.041)	(0.055)	(0.041)	(0.040)	(0.121)
4-star hotel	1.644***	3.182***	1.822***	2.045***	3.505***

Full demand estimates ◂ Back III

	(0.043)	(0.075)	(0.050)	(0.050)	(0.126)
5-star hotel	-0.210^{***}	4.326^{***}	3.206^{***}	3.482^{***}	4.468^{***}
	(0.066)	(0.176)	(0.114)	(0.111)	(0.165)
Log Airbnb offer					0.351^{***}
					(0.016)
Constant	-6.470^{***}	-6.031^{***}	-4.157^{***}	-4.307^{***}	-6.319^{***}
	(0.039)	(0.044)	(0.045)	(0.070)	(0.128)
Market FEs	N	N	N	Y	Y
N	33,504	33,504	33,504	33,504	33,504
Adjusted R^2	0.377	0.133	0.652	0.700	0.862

Full demand estimates ◂ Back IV

F-statistics

Back

Table 3: F-statistics

	(2)/(3) Logit/NL	(4) NL	(5) NL
Price	602.83	648.81	3631.20
σ_1	257.26	263.96	4906.98
σ_2	7636.45	8045.26	11793.30

Average estimated demand elasticities ◂ Back

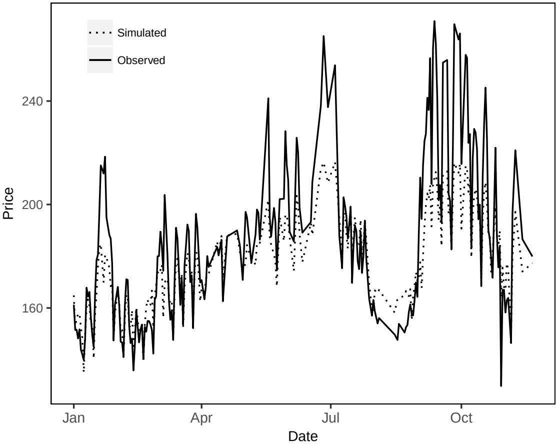
			Cross-price elasticities		
Type	Category	Own-price elasticity	Same district & Type	Same district	Other district
Airbnb	1	-0.5095	0.2548	0.0091	0.0007
	2	-0.9583	0.1744	0.0057	0.0004
	3	-1.3400	0.2387	0.0077	0.0006
	4	-2.4661	0.6033	0.0178	0.0014
Hotels	1	-1.3769	0.0669	0.0053	0.0005
	2	-1.6417	0.1310	0.0109	0.0011
	3	-1.6144	0.6378	0.0538	0.0054
	4	-2.6882	0.7415	0.0629	0.0060
	5	-7.4321	1.2201	0.1111	0.0120

Average estimated demand semi-elasticities ◂ Back

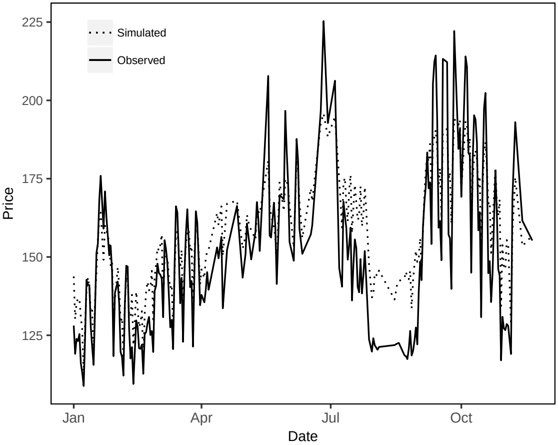
			Cross-price semi-elasticities		
Type	Category	Own-price semi-elasticity	Same district & Type	Same district	Other district
Airbnb	1	-1.3217	0.4591	0.0161	0.0013
	2	-1.5037	0.2771	0.0093	0.0007
	3	-1.4810	0.2998	0.0098	0.0008
	4	-1.4058	0.3750	0.0111	0.0009
Hotels	1	-1.6924	0.0884	0.0071	0.0007
	2	-1.6476	0.1332	0.0110	0.0011
	3	-1.2696	0.5112	0.0431	0.0042
	4	-1.3463	0.4345	0.0360	0.0033
	5	-1.3986	0.3822	0.0353	0.0039

Comparison Simulation vs. Observed Data

◂ Back ▸ Additional Checks

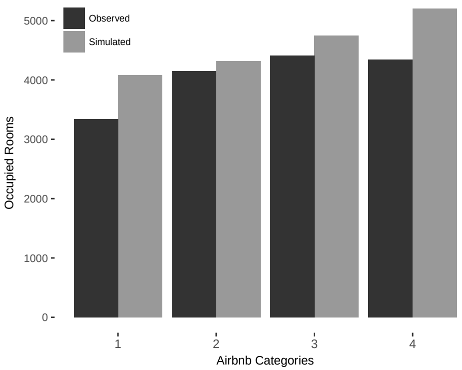


Hotel Prices - All hotels

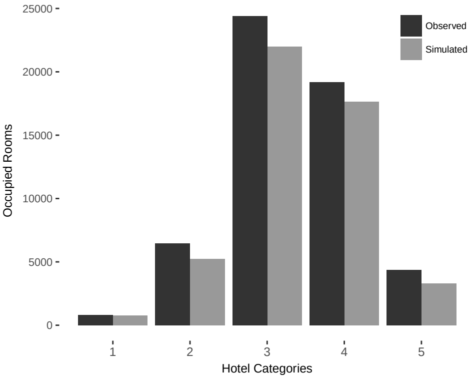


Hotel Prices – without 5 star

Simulated vs observed data I ◂ Back

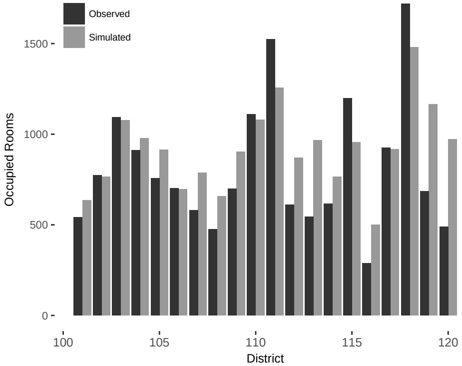


Airbnb demand by category

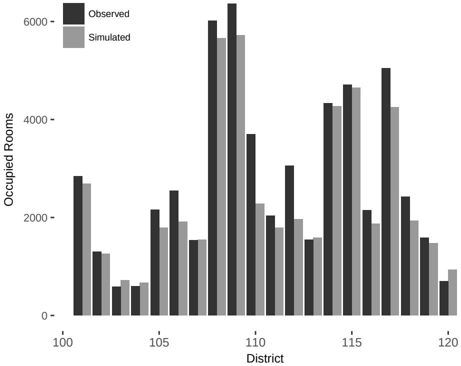


Hotel demand by category

Simulated vs observed data II ◂ Back

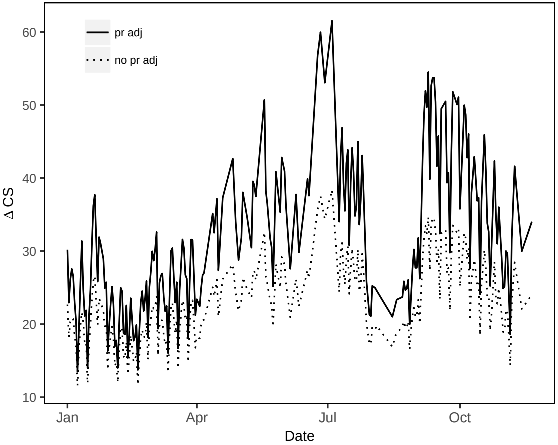


Airbnb demand by district

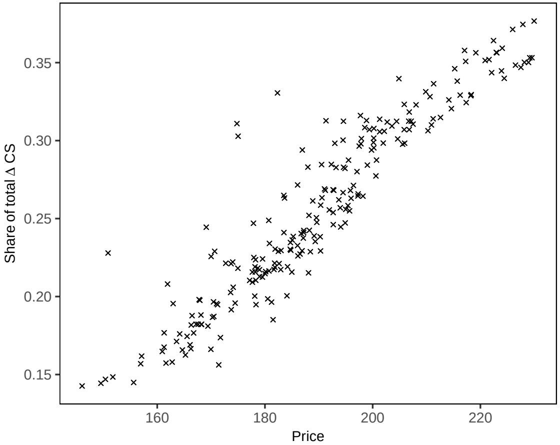


Hotel demand by district

Heterogeneity over Time ◂ Back

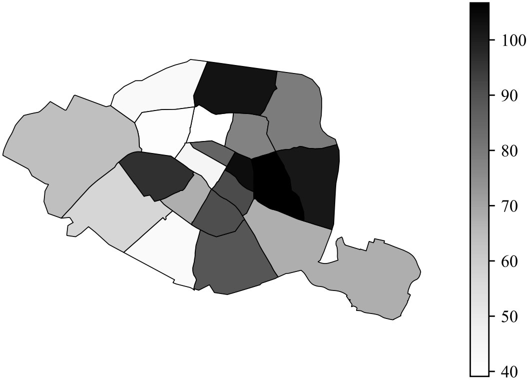


ΔCS per guest by date

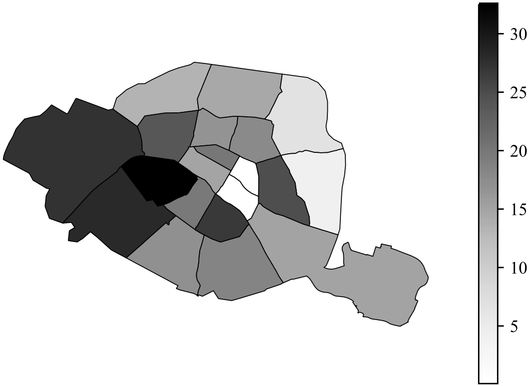


Share of ΔCS due to price adjustment by price

Heterogeneity by District ◂ Back



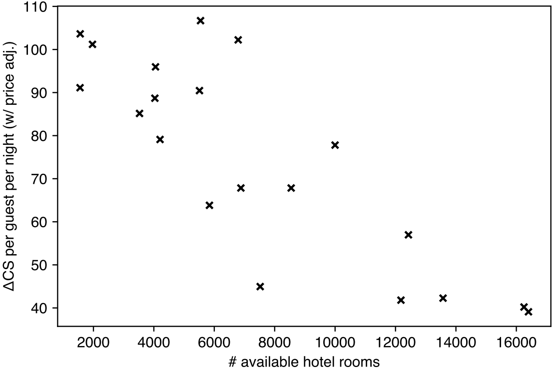
ΔCS per guest by district

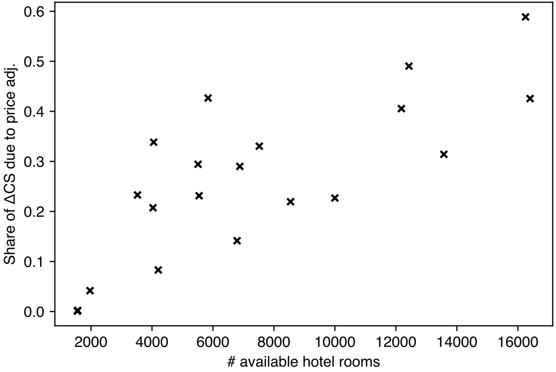


ΔCS due to price adjustment by district

Heterogeneity by District Hotel Offer

▸ By Airbnb share





Hotel Revenues

◂ Back

Star Category	Price	Δ Pr	Δ Pr %	Δ Q		Δ Q %	
				pr adj	no pr adj	pr adj	no pr adj
1	92.93	4.63	5.00	157.62	144.39	16.28	14.91
2	101.12	10.76	10.64	847.06	944.91	16.08	17.93
3	131.39	18.90	14.39	2269.21	3967.71	10.30	18.01
4	205.92	21.06	10.23	1478.53	3176.55	8.27	17.76
5	470.70	21.04	4.47	169.49	582.18	5.05	17.36

Heterogeneity by District Airbnb Share

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