Airbnb, Hotels, and Localized Competition

University of Bristol Applied Micro Brown Bag Seminar

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Intro

Motivation

- Sharing economy (Airbnb, Uber):
  - $+$ Benefits consumers through increased variety and lower prices
  - $-$ Lowers prices to the detriment of established industries
- Total welfare impact? $(+ > -)$ or $(+ < -)$?

This paper

- Question: Impact of Airbnb on consumer welfare and hotel revenues
- Method:
  - Estimate model of demand for short-term accommodation (hotel rooms or Airbnb listings)
  - Simulate prices and choices absent Airbnb
  - Compare consumer welfare and hotel revenues
- Setting: Paris, 2017

Related literature

- Competition Airbnb vs. hotels:
    - Zervas, Proserpio, and Byers [2017], Neeser [2015]
- Competition established industries vs. peer-to-peer platforms:
    - 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 [2020]
- Impact Airbnb on total welfare:
    - Farronato and Fradkin [2018]

Contribution

- Quantify welfare effect of Airbnb in the hospitality industry in Paris
- Novelty:
    - Account for geographic dimension of competition

  $\rightarrow$ Nearby units are closer substitutes

Preview of results

- Consumer surplus gain: 31 euro per traveller and night
- Aggregated by average number of travellers: 4.3 million euro per night
- Average hotel revenue loss: 1.8 million euro per night (≈ 15 percent)
- 72 percent of Airbnb bookings would not occur absent Airbnb

Presentation Plan

Data and Descriptives

Demand Model and Results

Welfare Effects of Airbnb

Conclusion

Data and Descriptives

Data

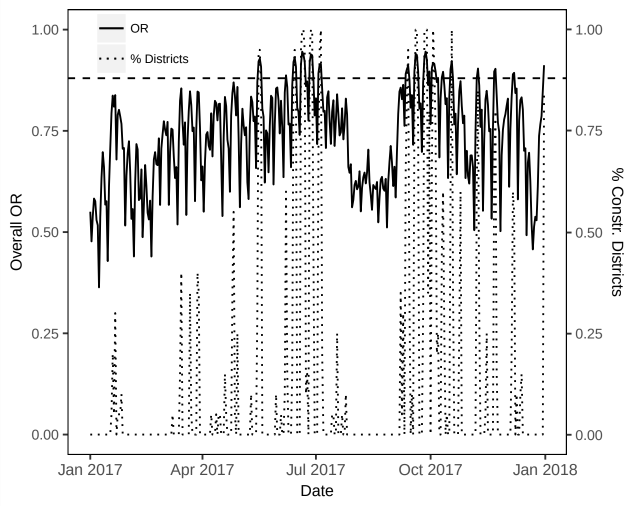
- Setting: Paris, 2017
- Accommodation-level data from three different sources:
  - Daily hotel occupancy data (INSEE)
  - Daily hotel price data [Hunold, Kesler, and Laitenberger, 2020]
  - Daily Airbnb occupancy and price data (Airdna)

→ Daily price and occupancy for each hotel and Airbnb listing

Data aggregation

- Aggregate data to define products as **Location–Type–Quality** combination
  - **Location:** Districts of Paris
  - **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...

Geographic hotel demand heterogenity



- OR: Occupancy Ratio (# occupied/ # available rooms)
- % Districts: % districts with OR > 0.9

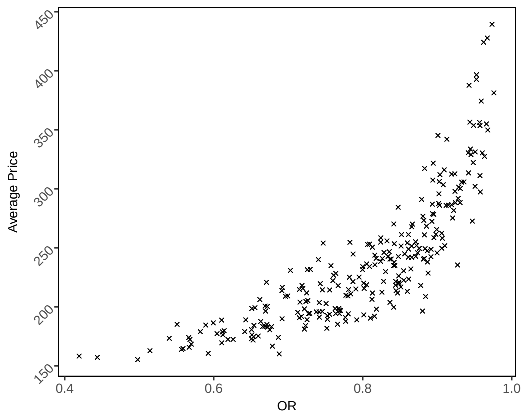


Figure 1: Typical Hotel Pricing

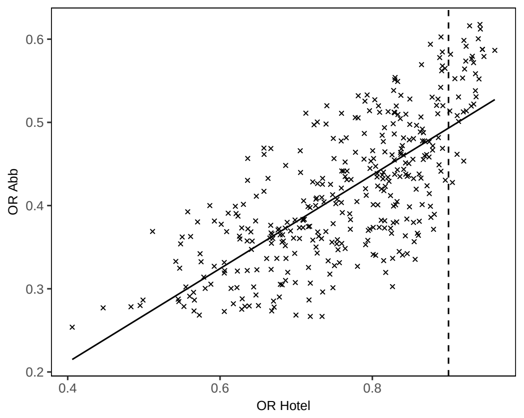


Figure 2: OR Airbnb vs hotels

Demand Model and Results

Two-level nested logit

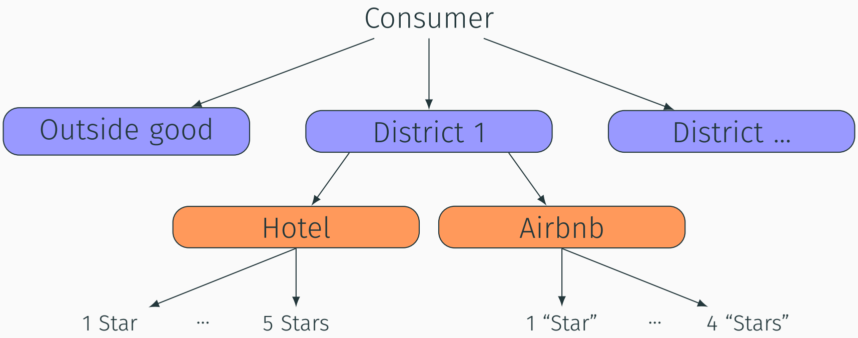


Figure 3: Sequential choice model

Estimation equation [Verboven, 1996]

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

- 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
- ϵ_t: time specific shock
- $0 \leq \sigma_2 \leq \sigma_1 \leq 1$

Market size

- Number of people looking for short-term accommodation in Paris (including those booking nothing/something unobserved $\rightarrow$ outside good)
- Measure
    1. Global Google trends data for the keywords "hotels Paris" and "Airbnb Paris"
    2. Add up both trends
    3. Set scale: average trend value $=$ average number of hotel and Airbnb rooms in 2017 ▸ Plot

Identification

- Two challenges for identification
    1. Endogeneity of prices and market shares
    2. Underlying capacities may affect market shares
- Two proposed solutions
    1. Instruments
    2. Accounting for capacities

Instrumental variables

- Central idea: Rivals' capacities influence pricing

$$z_{jt} = \sum_{l \neq j} \frac{c_{lt}}{e_{lj}^2}, \qquad (2)$$

  - Rival's capacity: c_{lt}, rival's distance: e_{lt}
  - For (I) same type and quality, (II) different type and same quality, and (III) different type and same district
  - Separate instruments for Airbnb and hotels
- Additional challenges
  1. Airbnb capacity is not exogenous to demand → create exogenous measure
     ▸ Capacity vs occupancy ▸ Airbnb short-term supply vs demand
  2. Hotel capacity is fixed → interact with Market Size: z_{jt}/MS_t

Airbnb supply instruments

- Idea: Predict variation in Airbnb supply due to factors exogenous to local, short-term demand shocks
- Exogenous predictors
  - Quartic time trend
  - Outgoing leisure-related traffic
    - Outgoing traffic at main highway exits on day before weekend/holiday minus average outgoing traffic during weekdays in preceding week
    - 0 for weekdays
- Prediction for each Airbnb product separately ▸ Example

Accounting for capacities

- Aggregate products $\rightarrow$ underlying capacities might vary $\rightarrow$ Market shares might reflect capacity constraints rather than demand
- Hotels: Supply almost constant
  - Fixed effect for districts with >2000 four- and five-star hotel rooms
- Airbnb: Supply varies
  - Include log of predicted exogenous Airbnb capacity [Ackerberg and Rysman, 2005]

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

Welfare Effects of Airbnb

Main ideas

- Goal: Consumer welfare and hotel revenues with and without Airbnb
- Airbnb benefits consumers
  1. More choice
  2. Competition $\rightarrow$ lower prices
- Following Farronato and Fradkin [2018]:
  - ΔCS w/o hotel-price adjustments $= \Delta$ from reduced variety
  - ΔCS w/ hotel-price adjustments $= \Delta$ (reduced variety $+$ higher hotel prices)
  - ΔCS w/ - ΔCS w/o $= \Delta$ from higher hotel prices
- Approach: Simulate prices and market shares with and without Airbnb

Airbnb supply

- Supply: Exogenous measure calculated for instruments
- Prices: Observed prices ▸ Airbnb vs hotel prices

Hotel supply

- Challenges
  - Capacity constraints: Discrete choice model assumes unconstrained capacity
  - Hotel pricing decision: Could take into account rival capacity constraints $\rightarrow$ complex to solve analytically

Equilibrium simulation

- Given price vector p, market size MS, and choice set $\mathcal{J}$
    1. Calculate demand $q_j(p)$ for hotel j
    2. If $q_j > k_j$ (capacity), remove hotel j from choice set $\mathcal{J}$ and go back to (1)
    3. Stop if $q_j < k_j \forall j$

Hotel prices

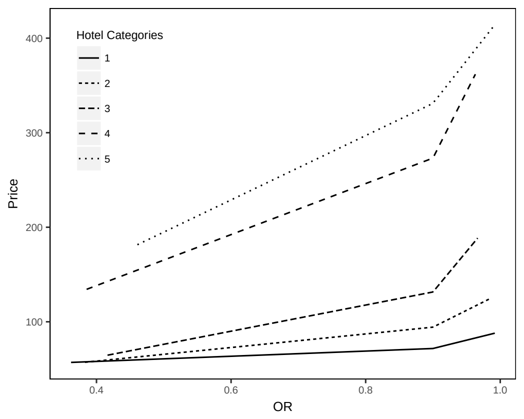


Figure 4: Estimated hotel pricing functions (example district)

- Estimate $p_j(q)$ (with kink)
- In iteration step κ, set some $\mathbf{p}^\kappa$
  1. Calculate $\mathbf{q}^\kappa = \mathbf{q}(\mathbf{p}^\kappa)$ as described
  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 $p_j(q_j^\kappa) \approx p_j^\kappa \forall j$

▸ Sanity checks

Consumer surplus

- Average gain in consumer surplus per consumer and night
    - Taking into account hotel price adjustment: 31 euro
    - Ignoring hotel price adjustment: 23 euro

  $\rightarrow$ Price effect $\approx$ 26 percent
- Multiplied by market size per night
    - Taking into account hotel price adjustment: 4.3 million euro
    - Ignoring hotel price adjustment: 3.1 million euro

Heterogeneity

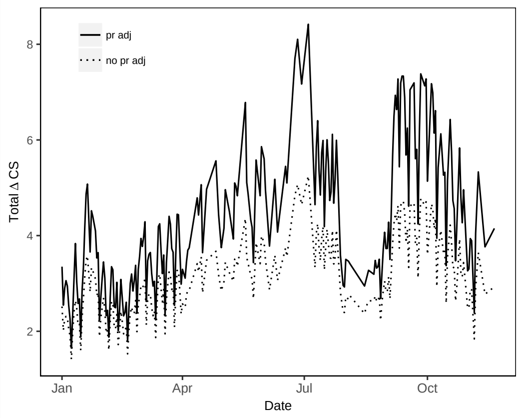


Figure 5: ΔCS by date

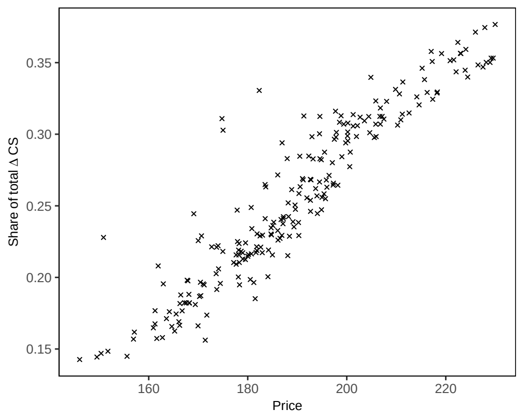


Figure 6: Share of ΔCS due to price adjustment over average price

Airbnb demand

- Minority of Airbnb consumers switch to hotels
  - With price adjustment: 28 percent
  - Without price adjustment: 48 percent

Hotel revenues

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

- Average aggregate daily revenue change: 1.8 million euro

Conclusion

Conclusion

- Consumer surplus from Airbnb: 31 euro per traveller and night
  - Average of 4.3 million euro per night
  - $\approx$ 26 percent due to competition ($p \downarrow$)
  - Pronounced in periods of high demand
- On average, Airbnb reduces hotel revenue by 1.8 million ($\approx 15\%$) euro per night.
- 72 percent of Airbnb consumers do not book absent Airbnb

Thank you!

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Appendix

Summary statistics

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)	-

Offer and occupancy ◂ Back

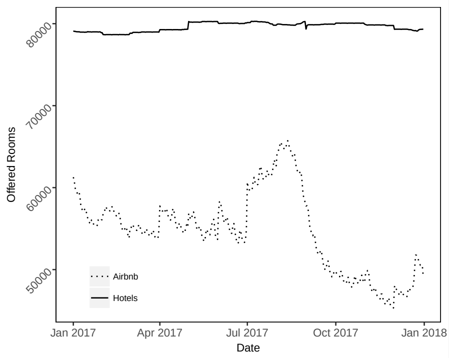


Figure 7: Offer

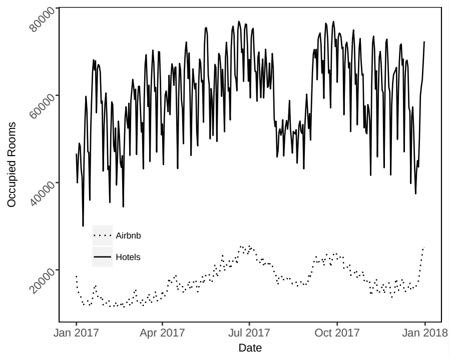


Figure 8: Occupancy

Endogenous Airbnb supply ◂ Back

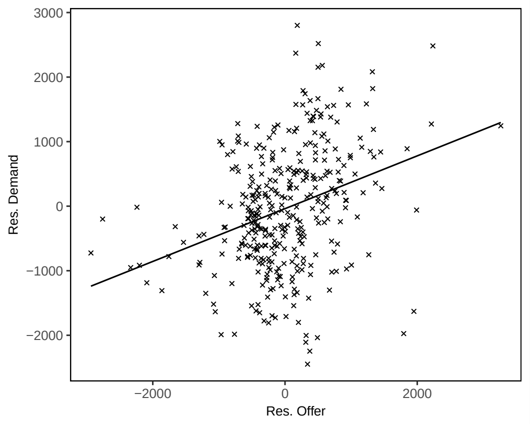


Figure 9: Short-term Airbnb demand and supply. Differences from 14-day moving averages. Each point is one date. Line is linear fit.

Airbnb vs. Hotel Prices ◂ Back

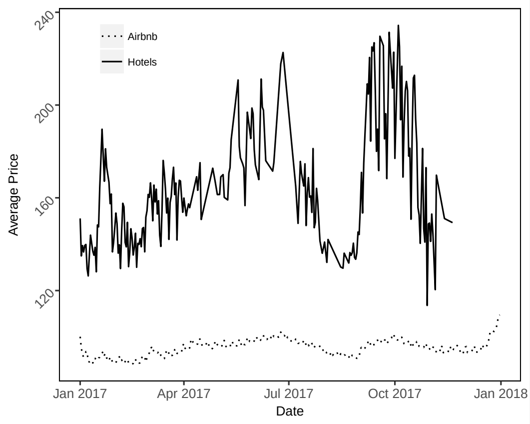


Figure 10: Airbnb and Hotel Prices over Time

Spatial Distribution

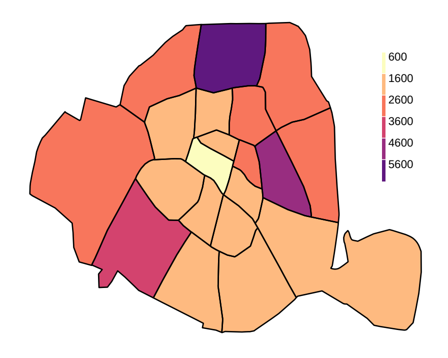
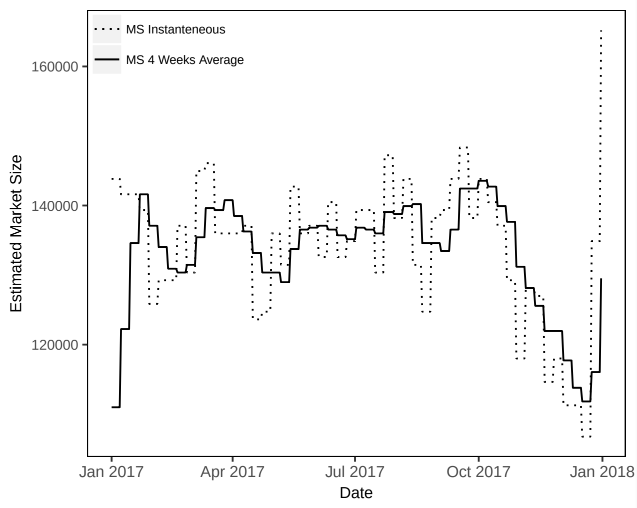


Figure 11: Airbnb

Figure 12: Hotels

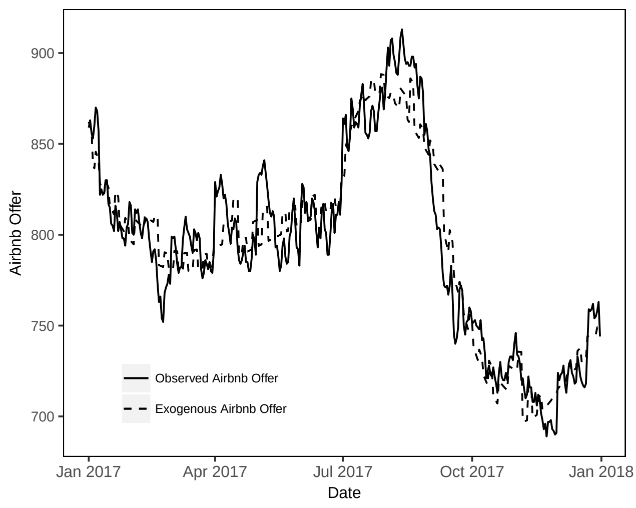
Market size

Back



Exogenous Airbnb supply

◂ Back



Full demand estimates ◂ Back i

Table 1: Parameter estimates corresponding to Table 19

	(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^{***}

Full demand estimates ◂ Back ii

			(0.010)	(0.009)	(0.006)
Airbnb category 2	0.290***	0.501***	0.068***	0.132***	−0.019*
	(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)

Full demand estimates ◂ Back iii

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^{***}
	(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)

Full demand estimates ◂ Back iv

Constant	-6.470^{***}	-6.031^{***}	-4.157^{***}	-4.307^{***}	-6.319^{***}
	(0.039)	(0.044)	(0.045)	(0.070)	(0.128)
Market FE	*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 v

F-statistics

Back

Table 3: F-statistics corresponding to Table 19

	(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

Simulated vs observed data I ◂ Back

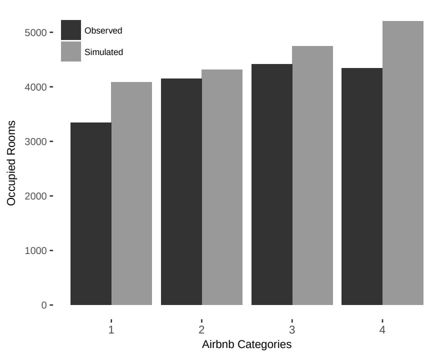


Figure 13: Airbnb demand by category

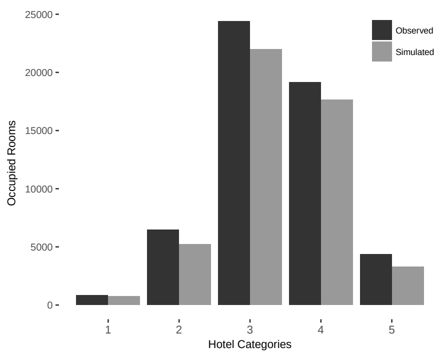


Figure 14: Hotel demand by category

Simulated vs observed data II ◂ Back

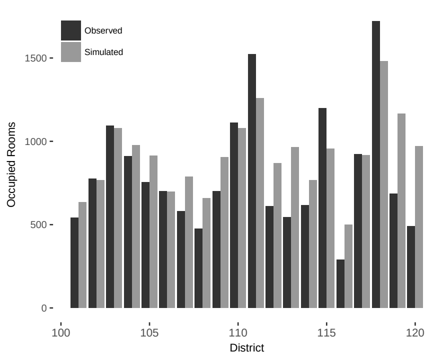


Figure 15: Airbnb demand by district

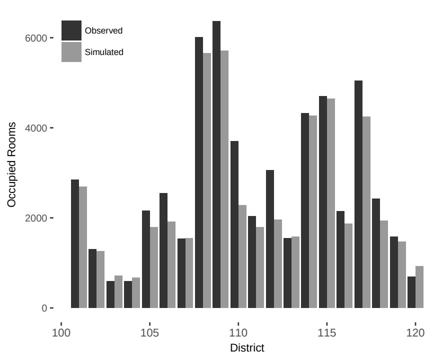


Figure 16: Hotel demand by district

Simulated vs observed data III

Back

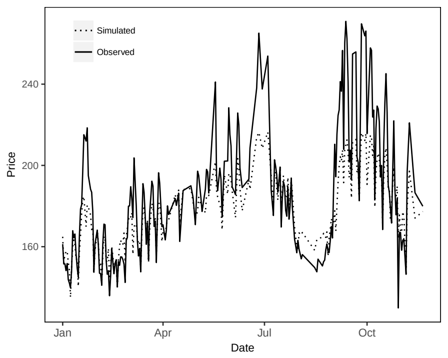


Figure 17: Hotel prices (sales weighted)

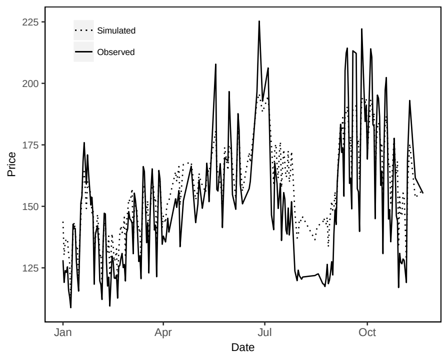


Figure 18: Hotel prices (sales weighted) - without category 5