Competitive Dynamics in the Sharing Economy: An Analysis in the Context of Airbnb and Hotels

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Abstract

The entry of flexible-capacity sharing economy platforms (e.g., Airbnb and Uber) has potentially changed the competitive landscape in traditional industries with fixed-capacity incumbents and volatile demand. Leveraging panel data on hotels and Airbnb, we study how the sharing economy fundamentally changes the way the industry accommodates demand fluctuations and how incumbent firms should strategically respond. The demand estimates suggest that Airbnb's flexible supply helps recover the lost underlying demand due to hotel seasonal pricing (i.e., higher prices during high-demand seasons) and even stimulates more demand in some cities. The counterfactual results suggest that some hotel types in some cities may benefit from conducting less seasonal pricing and even considering counter-seasonal pricing. Market conditions (e.g., seasonality patterns, hotel prices and quality, consumer composition, and Airbnb supply elasticity) play a crucial role in determining the impact of Airbnb on hotel sales and hotels' strategic response. Finally, recent Airbnb and policy changes (e.g., higher Airbnb hosting costs due to hotel taxes or lower Airbnb hosting costs due to third-party services and the "professionalism" of hosts) affect the competitive dynamics. The profits of high-end hotels are the most sensitive to the changes in Airbnb hosting costs. Airbnb's recent attempt to behave more like hotels can increase hotels' vulnerability to lower Airbnb hosting costs.

Key words: sharing economy, Airbnb, hotels, flexible capacity, seasonality

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1 Introduction

The sharing economy has grown at an exponential rate in recent years. Platforms such as Airbnb and Uber leverage under-utilized excess capacity in goods and services and allow for peer-to-peer exchange. In particular, they introduce flexible capacity (private cars on Uber and rooms on Airbnb) to traditional fixed-capacity markets (taxis and hotels). On the one hand, they help accommodate the highly volatile demand that is a common feature of these industries. On the other hand, they challenge the strategies of traditional firms that must pay high capital costs to add marginal capacity. These platforms have potentially changed the competitive landscape in these traditional industries, especially in markets with high demand fluctuations.

The travel and tourism industry is a typical example of a market that has been structurally affected. Seasonality is a fundamental feature of this industry. Given the capital-intensive nature of capacity, hotels use seasonal pricing to accommodate seasonal demand by charging higher prices during high-demand seasons. Airbnb was launched in 2008 and has become the largest home-sharing network, with more than three million listings worldwide.[1] It provides two ways to accommodate seasonal demand: both the supply and the pricing of Airbnb listings can vary across seasons. More listings during high-demand seasons can help amplify demand while higher prices during high-demand seasons can dampen demand. On the supply side, the flexible supply of Airbnb reduces the scarcity of capacity, mitigates hotels' abilities to extract higher prices during peak seasons, and challenges the conventional wisdom of capacity-driven hotel pricing strategy.

In this paper, we study the competitive dynamics of the sharing economy and the traditional economy in the context of Airbnb and hotels. The demand estimates illustrate how Airbnb fundamentally changed the way seasonal demand is accommodated in the travel industry. Using the demand estimates, we further examine how hotels should strategically respond by solving for the optimal supply-side strategies under current and counterfactual

[1] See `https://www.airbnb.com/about/about-us`.

scenarios. Hotel prices, Airbnb prices, and Airbnb supply are allowed to be endogenous in equilibrium. The counterfactual scenarios are motivated by recent Airbnb and public policy changes. First, the rapid growth in third-party services to support Airbnb (e.g., room cleaning and key exchange) has reduced the cost of hosting on Airbnb, while public policies such as hotel taxes have raised the cost of hosting on Airbnb. The first counterfactual varies the cost of hosting on Airbnb and explores its impact on equilibrium outcomes. Second, Airbnb is found to be more attractive to leisure travelers than to business travelers, as business travelers have specific requirements; 90% of Airbnb sales come from leisure travelers.[2]. The second counterfactual further removes business travelers' lower valuation of Airbnb as a result of Airbnb's recent attempt to act more similarly to hotels and provide standardized services using its "Business Travel Ready" program.[3].

Two demand model features are important for answering the research questions. First, seasonality is a fundamental driver of competition between fixed-capacity and flexible-capacity firms in this industry. We need to recover the underlying demand seasonality, which can vary across markets. This is challenging, as both demand and supply are seasonal in this industry; hotel pricing, Airbnb pricing, and Airbnb supply are endogenous to seasonal demand. The observed demand is a result of both the underlying demand and firms' seasonal conduct. We recover the underlying demand and use the control function approach (Petrin and Train 2010) to address the endogeneity of supply-side firm conduct. Second, consumer heterogeneity (i.e., the heterogeneous preferences of business and leisure travelers) is a critical feature of the industry and determines the competitive advantage of Airbnb versus hotels. We allow consumers to differ in their price sensitivity, preferences for particular hotel attributes (e.g., convention spaces and ski/spa/golf/boutique facilities), Airbnb types (e.g., hotel comparable or not), and propensity to travel to a particular city at a particular time of year (i.e., the underlying seasonality). Finally, to solve for the supply-side equilibrium, we obtain hotel costs from industry reports and estimate Airbnb host costs from the observed Airbnb supply and

[2]See https://bits.blogs.nytimes.com/2014/07/28/airbnb-expands-into-business-travel/.

[3]https://www.nytimes.com/2017/06/17/technology/airbnbs-hosts-professional-hotels.html.

data on host demographics, local housing conditions, and government regulations affecting Airbnb.

Our analysis gleans a number of insights.

1. Airbnb cannibalizes hotel sales, especially on the low end. Leisure travelers frequent Airbnb and cause market expansion.

We use the demand estimates to simulate market outcomes without Airbnb and find that Airbnb mildly cannibalizes hotel sales, especially for low-end hotels. The level of cannibalization can be related to market-specific attributes such as seasonality, hotel price and qualities, and consumer composition. We find suggestive evidence that cannibalization can be stronger in cities where 1) demand is more seasonal, 2) high-end hotel prices are lower, 3) the quality of low-end hotels is lower, or 4) the fraction of leisure travelers is higher. Leisure travelers are found to be more price sensitive, to value the ski/spa/golf/boutique facilities less, and to show strong seasonality in their propensity to travel. Their shift to Airbnb shows a 3.2 times greater reduction to hotel sales than that of business travelers. However, they also create a larger market expansion effect for the industry; most leisure travelers' Airbnb consumption comes from market expansion, while most business travelers' Airbnb consumption comes from cannibalizing hotels. We also find that business travelers have a lower valuation of Airbnb stays than leisure travelers do.

2. Airbnb mitigates the dampening of demand during peak seasons due to higher hotel prices.

In terms of seasonality and how Airbnb changes the way seasonal demand is accommodated in this industry, we find that the estimated underlying demand is more volatile and higher than the observed demand during high-demand seasons. The counterfactual results suggest that hotels' seasonal pricing (i.e., higher prices during high-demand seasons) dampens the underlying demand by 13.7%, on average. Airbnb's seasonal supply (i.e., more listings during high-demand seasons) has an amplifying effect and can help recover 67.5% of that loss or even stimulate more demand in some cities. However, with its seasonal pricing, only 34.3% of that loss is actually recovered. Overall, Airbnb still helps resolve the tension, albeit only partially, between cyclical demand and fixed hotel capacity and helps the industry better meet seasonal demand.

3. Flexible capacity may upend traditional pricing strategies in sharing markets. For some hotel types in some cities, an Airbnb presence may allow hotels to benefit from conducting less seasonal pricing or even from considering counter-seasonal pricing.

On the supply side, we find that it is optimal for some hotel types in certain cities to engage less in seasonal pricing or even to engage in counter-seasonal pricing. In particular, for Los Angeles, Chicago, and Seattle, mid-range and low-end hotels should exercise less seasonal pricing; for Miami and New Orleans, high-end hotels should exercise less seasonal pricing; for San Francisco, Washington D.C., and Austin, all hotel types should exercise less seasonal pricing. Hotels face the following trade-off: during peak seasons, higher demand provides incentives to raise prices, yet it also drives up Airbnb supply which may reduce competitive prices; in the off-peak seasons, softening demand provides incentives to reduce prices, yet it also reduces Airbnb supply which may increase competitive prices. Therefore, the significant price differences across seasons are more moderated. In fact, under certain conditions, counter-seasonal pricing may become optimal. We show that hotels may benefit from conducting less seasonal pricing and even from considering counter-seasonal pricing when 1) the hotel market share is smaller, 2) Airbnb's market share is larger, and 3) Airbnb's supply elasticity is greater. These conditions are more likely to hold for cities with the following market conditions, respectively: 1) higher hotel prices and lower hotel quality, a higher fractions of leisure travelers; 2) a stronger and longer presence of Airbnb; 3) a larger total number of potential hosts or a lower cost of hosting.

4. As Airbnb targets business travelers, high-end hotels are most affected. Regulations *that drive up the hosting cost on Airbnb enhance hotel profitability, but only up to a point.*

We further explore how recent Airbnb and public policy changes can affect the competitive landscape using three counterfactuals. In the first counterfactual, we vary the cost of hosting on Airbnb from 80% to 130% of its current value. In practice, the cost either increases due to more government regulations such as charging hotel taxes or decreases because of more third-party service providers (e.g., room cleaning and key exchange) and the trend of "professionalism" among hosts.[4] We find that hotel profits increase (decrease) as Airbnb host costs increase (decrease). Interestingly, high-end hotels benefit more from higher Airbnb host costs but also suffer more from lower Airbnb host costs. Another noteworthy finding is that the benefit of higher Airbnb host costs levels off as the costs increase while the loss from lower Airbnb host costs continues to decrease as the costs decrease. Therefore, imposing stricter regulations on Airbnb that raise the cost of hosting does not help hotel profitability beyond a certain point, yet reducing Airbnb host costs can increasingly hurt hotel profitability.

In the second counterfactual, we jointly examine the impact of varying the cost of hosting and Airbnb's attempt to appeal to business travelers by behaving more like hotels. We find that allowing Airbnb to behave like hotels (by removing business travelers' lower valuation of staying with Airbnb) makes hotels much more vulnerable to changes in Airbnb host costs; the impact of varying hosting costs increases dramatically once we remove business travelers' lower valuation of Airbnb. Hotel profitability can decrease by as much as 25% (when the cost of hosting is 80% of the current value) and increase by as much as 15% (when the cost of hosting is 130% of the current value). In practice, Airbnb is trying to reduce host costs and aims to offer more hotel-like standardized services. Both actions may be significantly detrimental to hotels in the long run.

This paper has managerial and policy implications for hotels, the travel industry, and other industries with flexible- and fixed-capacity firms. For hotels, we find that they may

[4] See `https://www.airbnb.com/help/article/653/in-what-areas-is-occupancy-tax-collection-and-remittance`, `https://learnairbnb.com/optimize-airbnb-save-time-money/`, and `https://skift.com/2014/05/30/the-professionalization-of-airbnb-hosts/`.

benefit from conducting less seasonal pricing and even engaging in counter-seasonal pricing. We show how the impact of Airbnb on hotel sales and hotel optimal strategies should vary across markets with different underlying seasonality patterns, hotel offerings, and Airbnb host costs. We further illustrate how hotels can be affected by recent policy changes and Airbnb's attempt to approach business travelers. For policy makers, Airbnb has been debated and regulated in the cities that it has entered. Our model can be used to predict whether and how much hotels will be affected even before Airbnb enters a city, given that city's pre-Airbnb seasonality patterns and hotel attributes. We also show that government regulations on Airbnb have differential impacts on different types of hotels; this impact can change given Airbnb's positioning towards business travelers. Finally, for other industries with fixed-capacity firms and volatile demand (e.g., taxi services), incumbent firms may also need to re-evaluate their strategies as flexible-capacity entrants (e.g., Uber) change the nature of competition.

2 Literature Review

This paper contributes to the literature on the role of seasonality and capacity on competition and firm strategy. Given seasonal demand, some industries exhibit seasonal strategies (e.g., Cooper and Haltiwanger 1993 on automobile supply, Einav 2007 on movie supply), while some industries exhibit counter-seasonal strategies (e.g., Warner and Barsky 1995 on grocery pricing). In particular, counter-seasonal pricing can be explained by a loss-leader strategy during high-demand seasons with intensified competition (Chevalier, Kashyap, and Rossi 2003), a lower aggregate price sensitivity (Nevo and Hatzitaskos 2006), or changes in the ability of firms to sustain implicit collusion (Rotemberg and Saloner 1986). In general, seasonal demand can provide mixed incentives for firms to price higher or lower. Sudhir et al. (2005) show that time-varying demand and cost have both a direct effect on prices (e.g., higher demand means higher prices) and an indirect effect on competition (i.e., higher demand causes more competition and lower prices).

We contribute to this literature by studying seasonal firm conduct in a new context where there is asymmetric competition between flexible-capacity firms (i.e., Airbnb) and fixed-capacity firms (i.e., hotels). The context is more complex, as there are three types of seasonal firm conduct (hotel seasonal pricing, Airbnb seasonal supply, and Airbnb seasonal pricing). Opposing impacts of seasonal demand on firm incentives are present in this context: higher demand directly raises prices so that firms have incentives to conduct seasonal pricing; higher demand also indirectly intensifies competition, as it induces a greater supply from the flexible-capacity firm so that firms have incentives to conduct less seasonal pricing. We study the novel pricing incentive due to the presence of a flexible-capacity sharing economy and empirically show that it is optimal for some firms in some cities to conduct less seasonal pricing and even to conduct counter-seasonal pricing.

This paper contributes to the recent literature on the sharing economy. In their pioneering work on Airbnb, Zervas, Proserpio and Byers (2017) study the impact of Airbnb's entry on hotels in Texas. They find that Airbnb mildly cannibalizes hotels, with lower-price hotels being the most affected. Our demand model builds on their work and further explores the roles of seasonality, business/leisure travelers, and hotel offerings in determining the impact across markets. We leverage data from multiple cities across the United States with various levels and patterns of seasonality.

On the supply side, there have been theoretical models on the implications of peer-to-peer sharing on product quality and distribution channel strategy (e.g., Jiang and Tian 2016, Tian and Jiang 2017). We contribute to the literature by studying optimal pricing and supply decisions and proposing novel strategies for incumbent fixed-capacity firms. We highlight the competition between fixed-capacity and flexible-capacity firms, which is a critical feature for many industries that have found themselves affected by the sharing economy.

3 Data

Airbnb was founded in 2008 and expanded rapidly at an exponential rate across the United States. Between 2014 and 2015, the number of listings doubled and accounted for more than 5% of the total available rooms in major cities (e.g., Los Angeles and San Francisco) and popular travel destinations (e.g., Miami and Austin) in the United States. By 2014, Airbnb's share of rooms was between 1% and 4% in most cities. Unlike hotels, which have fixed capacities and fixed costs that constitute 70% of total costs, Airbnb has flexible capacity, meaning that most of costs are variable.[5]

3.1 Data Description

We combine Airbnb and hotel data sets as well as information on market attributes such as the number of visitors and local rents.

The first data set includes listing-level Airbnb data from August 2014 to October 2015 in the United States, collected by a third-party company that specializes in data collection and analysis. During the sample period, 342,873 properties are listed on Airbnb. An advantage of our data set, compared with web-scraped Airbnb data, is that it contains both consumer-facing information, such as property characteristics, and backstage information, such as availability (i.e., open for booking) and booking information. The latter is crucial for accurately measuring Airbnb's supply and revenue. A property may be unavailable to consumers because the host chooses to block the calendar or the property has been booked. By observing both availability and booking information, we can effectively distinguish between the two cases. To compute Airbnb supply, we define active listings as the listings that are marked as either booked or available on the host's calendar. Inferring instantaneous Airbnb supply is a challenging task, even for Airbnb itself, due to stale listings: listings that seem available but are not because the hosts forgot to update the calendar (Zervas et al. 2017).

[5]See `http://businessecon.org/2014/10/heads-on-beds-hotel-management/` for a discussion on hotel cost composition.

We conduct robustness checks using different Airbnb supply definitions and find that the results are robust to the choice of definitions.[6] For each listing, we observe detailed information on characteristics, such as location, room type (entire home/apartment, private room, shared room), the number of reviews, the rating (overall and in terms of accuracy, communication, cleanliness, location, check-in process, and value), the response rate/time, room rules (e.g., no smoking or pets), and facility information (e.g., Internet, heating, kitchen, dryer, doorman, intercommunication system). The data company further categorizes the "entire home/apartment" listings into two groups based on their expertise in working with hotels and Airbnb hosts: hotel comparable and not hotel comparable. The homes/apartments that are comparable to hotels are entire residences, described as apartments, condos, bed and breakfasts, lofts, bungalows, dorms, or townhomes, with 3 or fewer bedrooms.

The second data set includes the hotel data from January 2008 to October 2015, collected by Smith Travel Research (STR).[7] It contains the number of hotels and individual hotel attributes, such as location, scale (luxury to economy), the number of rooms, and facilities (e.g., restaurants, convention spaces, skiing, spas, golf, boutiques, and all suites). It also contains hotels' monthly prices, occupancy rates, and revenues, aggregated at the tract-scale level. A tract is a zip code-based sub-area within a city and is defined by STR based on hotel industry needs and customer input. We have data on 51 tracts in eight representative cities: Los Angeles, San Francisco, Washington, D.C., Miami, Chicago, New Orleans, Austin, and Seattle. These cities represent different regions of the United States, have different observed demand seasonality patterns, and have sufficient and varying levels of Airbnb presence. There are 4,943 hotels that have ever operated in these cities. Among them, 171 hotels (3.4%) shut

[6] To address potential stale listings, we run two robustness checks. In the first one, we exclude listings that appear to be available but have not been booked in the past three months (e.g., to calculate Airbnb supply in April, we exclude listings that appear to be available in April but were not booked in January, February, and March). Since stale listings cannot be booked, we believe that past booking information can be a proxy for listing activeness. In the second one, we assume that 25% of the listings are stale based on the estimates in the extant literature and randomly exclude 25% of the listings. For both robustness checks, we obtain very robust estimates.

[7] See STR Census Database (`http://www.str.com/products/census-database`) for hotel attributes and Trend Reports (`http://www.str.com/products/trend-reports`) for hotel performance.

Table 1: Summary Statistics

Hotel		H1		H2		H3	
	N	Mean	Std	Mean	Std	Mean	Std
Number of Hotels	51	15.0	(19.5)	26.9	(12.1)	39.2	(23.4)
Restaurant (%)	51	88.0	(21.7)	41.0	(16.4)	13.0	(9.6)
Convention Space (%)	51	19.5	(15.9)	1.1	(2.1)	0.1	(0.7)
Ski/Spa/Golf/Boutique (%)	51	36.1	(33.6)	7.1	(10.2)	0.9	(0.2)
All Suites (%)	51	17.6	(18.8)	22.9	(11.2)	13.2	(15.7)
Price ($)	3825	168.3	(46.4)	118.9	(28.1)	76.5	(23.8)
Occupancy Rate (%)	3825	71.3	(11.4)	69.7	(12.0)	64.8	(12.7)

Notes: "H1, H2, and H3" represent high-end, mid-range, and low-end hotels, respectively. The upper panel shows the time-invariant variables for 51 tracts. The lower panel shows the time-varying variables for 51 tracts over 75 months.

Airbnb		A1		A2		A3	
By Type	N	Mean	Std	Mean	Std	Mean	Std
Number of Listings	765	114.2	(148.1)	259.3	(458.6)	191.1	(230.2)
Price ($)	765	222.1	(80.3)	137.3	(53.4)	72.8	(17.9)
Number of Bedrooms	765	2.35	(0.58)	1.26	(0.40)	1.00	(0.00)
Number of Bathrooms	765	1.75	(0.39)	1.19	(0.27)	1.15	(0.10)

All types	N	Mean	Std		N	Mean	Std
Rating	2295	4.67	0.50	Internet (%)	2295	75.3	15.1
Number of Reviews	2295	25.5	13.2	Smoking (%)	2295	4.47	4.86
Heating (%)	2295	91.2	13.8	Pets (%)	2295	20.1	12.8
Kitchen (%)	2295	88.7	13.6	Doorman (%)	2295	3.76	8.42
Dryer (%)	2295	74.6	15.5	Intercom (%)	2295	9.5	10.9

Notes: The tables show the average monthly values for the variables for 51 tracts over 15 months by room type (upper table) and for all types (lower table). "A1, A2, and A3" represent an entire home/apartment that is not hotel comparable, an entire home/apartment that is hotel comparable, and a private room, respectively.

down during the sample period, 112 of which were economy-class hotels. No changes in hotel attributes occurred over time during the sample period. We use data on the hotels that remain open throughout the sample period to estimate the model.

To combine the two data sets, we average over the Airbnb listings in each tract and obtain the listing attributes and performance at the month-tract level. We focus on three types of hotels (high-end, mid-range, and low-end, which correspond to luxury/upper upscale, upscale/upper midscale, and midscale/economy classes, respectively, in the hotel data) and three types of Airbnb rooms (entire homes/apartments that are not hotel comparable, entire homes/apartments that are hotel comparable, and private rooms). The fourth type of Airbnb room, the shared room, accounts for less than 1% of all listings. Table 1 shows the summary statistics for hotels and Airbnb by room type at the month-tract level. Compared with low-end hotels, high-end hotels are more expensive and are more likely to have a restaurant, a convention space, skiing, a spa, and golf facilities. These facilities are widely used in the hotel industry for rating purposes and can proxy for the quality of hotels.[8] High-end hotels are also more likely to have slightly higher occupancy rates than low-end hotels. The most common Airbnb room type is the hotel-comparable entire home/apartment. The most expensive and the most spacious Airbnb room type is an entire home/apartment that is not hotel comparable. Over 70% of Airbnb listings have heating, a kitchen, a dryer, and Internet access. Smoking is allowed in fewer than 5% of the rooms, and pets are allowed in only 20% of the rooms.

Finally, we collect the number of visitors by air per month for each city from the T-100 Market (All Carriers) database to impute the potential market size.[9] We obtain hotel marginal cost data from industry reports. We first obtain the cost per-occupied-room night, \$42.20, which includes room cleaning and other administrative costs (HOST Almanac 2017 by STR). This figure is the average marginal cost across hotel types and markets. To obtain hotel type-specific costs, we refer to a popular hotel management text, which suggests \$20 per night for economy hotels and \$75 for luxury hotels (Rutherford, 2002, p. 323). We further adjust these costs by market-specific wages to reflect different costs across markets. Specifically, we obtain market-specific wages in the service industry from the American Community Survey (2015). We assume that the ratio of the market-specific wage to the average wage (computed by averaging over the market-specific wages) is the same as the ratio of the market-specific cost to the average cost. This assumption allows us to impute the market-specific costs.

[8] Hotel ratings are often used to classify hotels according to their quality. For how facilities are used to define quality and rating, see for instance the criteria for the diamond system in the U.S. by AAA (American Automobile Association) `http://aaa.biz/approved/assets/diamond_rating_guidelines_lodging.pdf`.

[9] See `http://www.transtats.bts.gov/Fields.asp?Table_ID=310`.

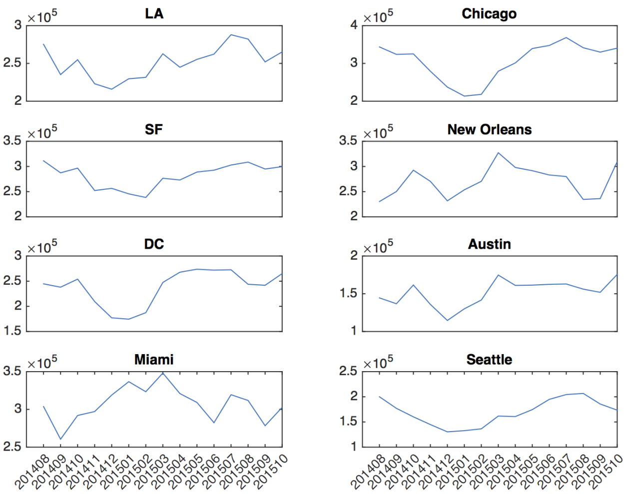
We also collect data on how friendly city policies are to short-term rentals (R Street Institute) and local demographics and housing information from the American Housing Survey.[10] These variables are used as instruments in the demand estimation and used as controls in the supply-side Airbnb hosting cost estimation. The American Housing Survey is the most comprehensive national housing survey in the United States. It contains property-level property usage information (rented out, owner occupied, or vacant) and owner demographics such as age, income, presence of children, marital status, education, and unemployment rate. Rented-out properties could be potential Airbnb listings and are relevant for our analysis. We use the property usage information to construct the tract-level rent-to-own ratio (the number of rented properties over the number of owner-occupied properties) and the total number of rented properties. We average over the rented-out properties in the same tract to construct tract-level host demographics data. To measure friendliness of city policies for short-term rentals, we use scores from the R Street Institute for the following five aspects: legal framework for regulations, legal restrictions, tax collection obligations, licensing regime, and enforcement regime. We keep all but the third aspect because there is no data variation on tax collection across the eight cities that we study. Cities with more favorable policies receive higher scores.

3.2 Data Patterns

Seasonal Demand, Supply, and Pricing This industry is characterized by the strong seasonality of demand. Figure 1 plots the observed average month-tract level total demand in this industry between August 2014 and October 2015 across cities. All data in the figures and tables are at the **tract** level, averaged across the tracts in each city, to be consistent with the empirical model analysis. Demand is highly seasonal in all cities. We also plot the demand for hotels and Airbnb separately. Both of them exhibit highly seasonal patterns. Airbnb demand has an additional growing trend over time. In addition to seasonality, the

[10] See `https://www.census.gov/programs-surveys/ahs.html` and `http://www.roomscore.org/`.

Figure 1: Seasonal Demand



data show a growing demand trend over time, starting in 2008, as the economy recovers from the financial crisis. Figure 2 plots the observed monthly hotel demand in Miami from 2008 to 2015. We normalize the demand using the first-period value to focus on the growth pattern over time. Demand is growing over time, especially for high-end and mid-range hotels.

The supply-side strategies in this industry are also seasonal and closely follow the seasonality of demand. Figure 3 plots the monthly tract-level hotel demand, hotel prices, Airbnb demand, Airbnb supply, and Airbnb prices in Los Angeles. We normalize each variable by its average value across time to focus on the seasonality patterns. We find that hotel pricing, Airbnb pricing, and Airbnb supply closely follow the seasonality patterns of demand; Airbnb supply and demand exhibit another growing trend over time, reflecting the platform's growth. Although not presented here, tracts within the same city share the same seasonality patterns. At the individual listing level, there is seasonality in Airbnb prices as well. We examine properties that appeared for more than three months (as a cumulative number; time gaps between months were allowed) in the data and find that 85.4% of them have price adjustments over time, including both positive and negative price adjustments. Properties with one or two months of presence are not examined because they may not experience seasonal demand changes and thus do not need to adjust their prices.

Figure 2: Seasonal Hotel Demand over Time: Miami

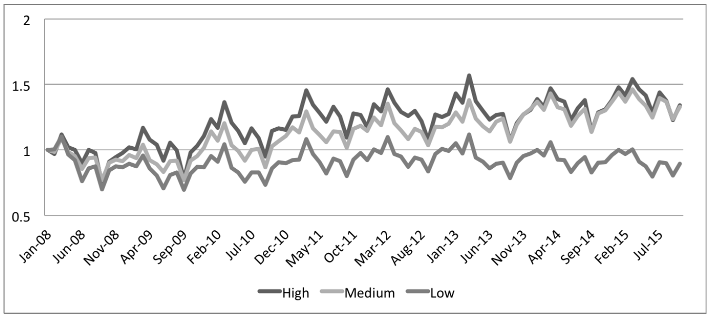
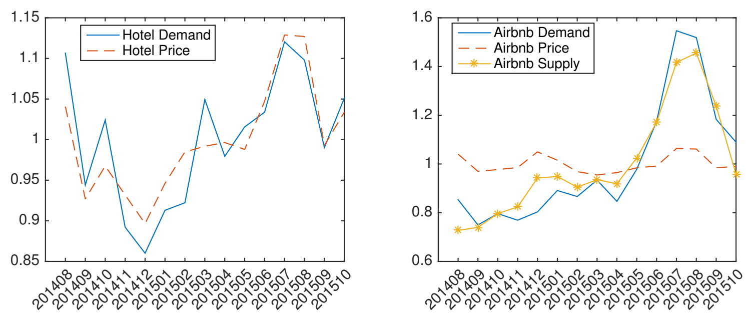


Figure 3: Seasonal Demand, Pricing, and Supply



Notes: We normalize each variable by its average value across time to focus on the seasonality patterns.

Market Differences Cities differ in both the degree and the pattern of seasonality. As shown in Figure 1, the peak season is summer in Chicago and Seattle, while it is fall and spring in New Orleans and Austin. The variance in demand is largest in Miami and New Orleans and smallest in San Francisco. Cities also differ in terms of the Airbnb presence, as shown in Figure 4.

Cities have different hotel attributes and market shares. Table 2 presents the average tract-level hotel quantities, quality, prices, and market shares. Miami has the most high-end hotels (31.0), and Los Angeles has the most low-end hotels (65.1). In absolute terms, the most expensive high-end hotels are in San Francisco, while the most expensive high-end hotels relative to low-end hotels are in Austin. As for facilities, 28.1% of high-end hotels in New Orleans have convention spaces, while only 12.4% of high-end hotels in Austin have convention spaces; 82.5% of high-end hotels in Miami have ski/spa/golf/boutique facilities, while only 18.5% of high-end hotels in Chicago have such facilities. The differences in hotel

Figure 4: Seasonal Airbnb Supply: by City

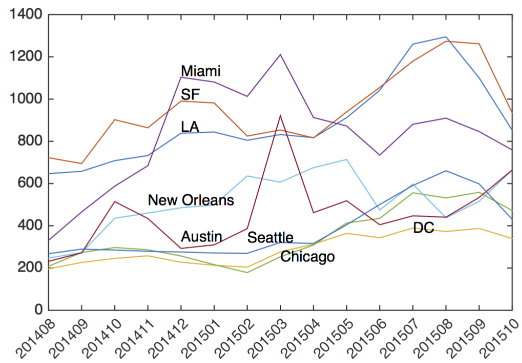


Table 2: Hotel Differences across Cities

	Number of Hotels			Prices ($)			Convention Space (%)			Ski/Spa/Golf/ Boutique (%)			Market Share (%)		
	H1	H2	H3	H1	H2	H3	H1	H2	H3	H1	H2	H3	H1	H2	H3
LA	14.4	20.2	65.1	180	123	77	25.6	1.8	0.4	34.9	8.8	0.3	36	28	36
SF	21.4	24.4	33.6	202	133	95	18.1	0.0	0.0	55.0	10.4	1.0	55	25	20
D.C.	13.8	31.0	25.5	166	125	78	15.7	0.5	0.0	21.1	1.5	0.6	43	39	18
Miami	31.0	34.8	34.3	185	128	91	21.7	2.1	0.0	82.5	30.3	5.8	43	33	24
Chicago	14.8	33.5	43.8	132	106	64	23.0	1.5	0.3	18.5	7.0	0.5	43	34	23
New Orleans	18.0	36.0	39.0	157	107	78	28.1	0.6	0.0	34.3	2.4	0.0	43	37	20
Austin	7.0	21.2	29.2	174	111	66	12.4	0.0	0.0	31.8	0.9	0.0	27	38	35
Seattle	7.8	19.8	29.5	165	117	74	12.7	1.8	0.0	44.8	2.5	0.5	30	43	27

Notes: "H1, H2, and H3" represent high-end, mid-range, and low-end hotels, respectively.

attributes and hotel market shares illuminate the intrinsic differences in visitor composition across these markets. As we will show later, these differences lead to different impacts of Airbnb on hotels and competitive dynamics.

4 Empirical Model

4.1 Model Setup

We use a nested logit specification with an emphasis on seasonality. The time period is a month. There are four seasons in a year—spring (February to May), summer (June to August), fall (September to October), and winter (November to January)—which are defined based on observed seasonality patterns and industry practice. Seasonality is captured by market-season dummies to allow for different seasonality patterns across cities.[11] There are three types of hotels (high-end, mid-range, and low-end) and three types of Airbnb rooms (entire homes that are hotel comparable, entire homes that are not hotel comparable, and private rooms). Let $j = 1, 2, 3, 4, 5, 6$ denote the six products, and $j = 0$ denote the outside option. Consumers only choose among hotel options during the pre-Airbnb period (2008–2012) when there is little to no Airbnb presence and choose among all options during the post-Airbnb period (August 2014–October 2015). We do not use hotel data from January 2013 to July 2014 in the estimation, as the presence of Airbnb is non-negligible and we do not have Airbnb data for that period. We define the total market size for each tract as three times the maximum number of monthly visitors by air in the data sample period. We provide details on why this definition is chosen and how it is calculated in the appendix. We also run robustness checks by varying the multiplier (two times or four times the maximum number of visitors by air) and show in the appendix that the results are very robust to the choice of the multiplier. The total potential market size includes consumers who actually travel and those who may not travel but who have an interest in traveling. We use the same value for the market size for all seasons and let the time-varying underlying seasonality fixed effects capture people who have an interest in travel if the accommodation options are attractive. The outside option is either not to travel or to travel but not stay in a hotel or Airbnb. The definitions of the market size and the outside option allow us to capture the effect of Airbnb's market expansion to two potential consumer groups: 1) people who travel but find the accommodations not attractive and choose to stay elsewhere; and 2) people who do not travel because of unattractive accommodation options. Including 2) is important, as Airbnb claims that a large number of its customers would not even have made the trip if Airbnb did

[11] We use season-level fixed effects because months in the same season generally have similar demand levels as shown in the data. These fixed effects are able to capture the average demand for months within the same season. They may not accurately capture the demand for a particular month if the underlying demand in that month is substantially higher or lower than the other months in the same season.

not exist.[12]

Let superscript A denote Airbnb and superscript H denote hotels. Let subscript M denote markets/cities and m denote tracts within markets. The utility that consumer i obtains from product j in tract m at time t is

$$\begin{aligned} u^H_{ijmt} &= \theta_j + \beta^H_i x^H_{jmt} + \alpha_i p^H_{jmt} + \gamma_{0j} n^H_{jmt} \\ &\quad + \tau_{iMt} + \beta_{T1} T_t + \beta_{T2} T_t^2 + \sigma \zeta_{imt} + \epsilon_{ijmt}, \qquad j = 1,2,3 \\ u^A_{ijmt} &= \theta_j + \theta^A_{ij} + \beta^A x^A_{jmt} + \alpha_i p^A_{jmt} + \gamma_{1j} n^A_{jmt} + \gamma_{2j} \left(n^A_{jmt}\right)^2 \\ &\quad + \tau_{iMt} + \beta_{T1} T_t + \beta_{T2} T_t^2 + \beta_{TA} T^A_{Mt} + \sigma \zeta_{imt} + \epsilon_{ijmt}, \qquad j = 4,5,6 \\ u_{i0mt} &= \epsilon_{i0mt} \end{aligned} \tag{1}$$

where θ_j represents the product fixed effects. x^H_{jmt} represents hotel characteristics such as restaurants, convention spaces, ski/spa/golf/boutique availability, and all suites. x^A_{jmt} covers Airbnb characteristics such as the number of bedrooms and bathrooms, ratings, the number of comments, kitchen/heating/dryer availability, and the presence of a doorman/intercom system. n^H_{jmt} and n^A_{jmt} are the numbers of available hotels and Airbnb listings. The quadratic term $\left(n^A_{jmt}\right)^2$ is included to capture any non-linear impact of listing availability; it allows the marginal utility from additional listings to change as the total number of listings increases. τ_{iMt} are the market-season fixed effects, which capture the underlying seasonality of demand, i.e., the attractiveness of these markets to consumers at different times of the year. Markets can have different seasonality patterns. Tracts in the same market share the same seasonality variables. These market-specific seasonality fixed effects capture the main variation in unobserved demand in the travel industry (due to seasonal vocational travel and business travel). These unobservables are at the heart of the endogeneity problem, and fixed effects are used to explicitly control for the part of the endogeneity issue that arises from the season of the year. The idiosyncratic error term has two components, $\epsilon_{ijmt} = \epsilon^1_{ijmt} + \epsilon^2_{ijmt}$, where ϵ^1_{ijmt} is correlated with price and supply and causes the remainder of the endogeneity prob-

[12]See `http://insights.wired.com/profiles/blogs/the-sharing-economy-q-a-with-airbnb-s-chip-conley`.

lem, and ϵ^2_{ijmt} is an i.i.d. extreme value error. The linear and quadratic yearly time trends $\{T_t, T_t^2\}$ capture consumers' willingness to travel over time, which is related to exogenous economic conditions or time-specific unobserved demand trends. In a robustness check, we allow for market-specific linear and quadratic trends. The trend estimates are not statistically significantly different across markets, so we keep the original specification. The reason might be that the time trend captures the increase in consumers' willingness to travel due to the economic recovery from the financial crisis in 2008; since travelers come from all over the U.S., this trend is shared across cities. We also plot the observed number of room-night stays by city and find a clear upward-sloping trend that is shared by all cities. Finally, the market-specific linear time trend of Airbnb T^A_{Mt}, measured by the number of months since Airbnb reached 5% of the total (hotel and Airbnb) rooms in a city, captures the potential awareness and acceptance of Airbnb in that city.

Consumers are heterogeneous in their preferences for particular hotel characteristics, Airbnb room types, price sensitivity, and underlying seasonality of demand patterns. This heterogeneity is modeled using a finite mixture structure, with a mixture-of-normals structure for some coefficients. The number of segments is estimated from the data (our estimates show that only two segments have empirical support, as the model with more than two segments is rejected). Let subscript i denote the heterogeneous types and γ_{iM} denote the fraction of segment i in market M ($\sum_i \gamma_{iM} = 1$). We allow the fractions to differ across cities as different cities may attract different types of consumers. Consumers might value hotel characteristics differently and have different price sensitivities. We allow the coefficients for two of the four hotel attributes, convention spaces and ski/spa/golf/boutique availability, to be a mixture of normals as $\beta_i^H = \left\{\beta_i^{conv}, \beta_i^{spa}, \beta^H\right\}$. The coefficients are assumed to be i.i.d. normally distributed as $\beta_i^{conv} = \bar{\beta}_i^{conv} + \sigma^{conv}\eta_i^{conv}$ and $\beta_i^{spa} = \bar{\beta}_i^{spa} + \sigma^{spa}\eta_i^{spa}$, where η_i^{conv} and η_i^{spa} are standard normal errors. The price sensitivity α_i can take two levels for the two types.[13]

[13]Following Train (2000), we keep the price coefficient fixed and do not model it as a normally distributed

We further allow consumers to differ in their propensity to travel during the year, as heterogeneous consumers may travel for different purposes that are served better by different seasons. We normalize the underlying seasonality of segment 1 to zero ($\tau_{iMt} = 0$ if $i = 1$) and estimate the underlying seasonality of the other segments.[14] Finally, consumers might be accepting of different Airbnb room types. We estimate segment-specific product fixed effects for Airbnb room types θ_{ij}^{A} in addition to the baseline fixed effects θ_j. The segment-specific product fixed effects are normalized to 0 for one of the segments.

We use a nested logit structure because it is able to better capture the market expansion effect. The six room types form one nest, and the outside option forms the other nest. ζ_{imt} is an i.i.d. standard normal error, which is common across room types. It captures consumers' idiosyncratic propensity to travel at time t, in addition to the regular seasonality patterns. The coefficient σ is the correlation across nests. If $\sigma = 0$, we obtain the simple logit model. As σ approaches one, there is perfect substitution within the nest and no substitution between the outside good and the inside good; hence, there is no market expansion effect.

4.2 Model Seasonality and Control for Endogenous Variables

We highlight how our model extends the traditional nested logit models to account for the seasonality of demand and supply, an important and unique feature of the travel industry. First, the model estimates the underlying demand that is seasonal and independent of supply-side seasonal strategies; this represents the pure attractiveness of visiting a particular city at a particular time of the year. Second, the model allows for seasonality in consumer preferences. For instance, consumer preferences for quality (price sensitivity) might be lower (higher) during summer, as more casual travelers are visiting the city. Although the overall

coefficient for the following reasons: (1) As Ruud (1996) points out, mixed logit models tend to be unstable when all coefficients are allowed to vary; (2) allowing the price coefficient to vary makes evaluating the distribution of willingness to pay difficult, as it becomes a ratio of two distributions; and (3) the distributional choice (e.g., normal or log-normal) for a price coefficient often leads to unattractive results.

[14] We perform this normalization because the variation in the data does not allow us to jointly estimate underlying seasonality across multiple segments.

fraction of heterogeneous consumers λ_{iM} is fixed over time in the entire population, the realized fraction is allowed to be endogenous to consumer choices. Notably, λ_{iM} is estimated rather than derived from additional data sources, as the observed fraction is influenced by supply-side strategies.

Third, we use the control function approach to address the endogeneity of seasonal supply-side variables (Petrin and Train 2010). Hotel prices p^H_{jmt}, Airbnb prices p^A_{jmt} and Airbnb supply n^A_{jmt} are highly seasonal, and all might be endogenous to unobserved demand shocks. We use market-specific seasonality fixed effects to control for the main unobserved demand shocks that are related to the time of year. In addition, we use the control function approach to explicitly account for the remaining endogenous component. In the first step, the endogenous variable is regressed on observed choice characteristics and the instruments. The residuals of this regression represent the component correlated with unobserved demand shocks, and these residuals are retained. In the second step, the choice model is estimated with the retained residuals, which are entered as extra variables.

The control function for Airbnb supply is

$$n^A_{jmt} = \rho_{1j} D_m + \rho_{2j} E_M + \tau^n_{Mt} + \mu^n_{jmt} \tag{2}$$

where the current period's supply is a function of market-specific controls D_m (instrument), city-level Airbnb regulations E_M (instrument) and seasonality fixed effects τ^n_{Mt}. The market-specific controls include tract-level age, income, percent with children, percent married, education, unemployment rate, and rent-to-own ratio from the American Housing Survey. The city-level Airbnb regulation variables include scores on how friendly city policies are to Airbnb along four dimensions. These instruments potentially affect hosts' incentives to list on Airbnb, while they do not directly affect demand. The error term is allowed to be correlated with ϵ^1_{ijmt} in the utility function in Equation 1. The market-specific seasonality fixed effects control for the unobserved demand shocks that are associated with the time of the year and that drive both Airbnb supply and total demand (e.g., seasonal vocational and business travel, annual music festivals, conferences, and commencement ceremonies). These shocks are the main unobserved demand driver in the travel industry.

The control functions for Airbnb and hotel prices are

$$p^{A}_{jmt} = \delta_{1j} x^{A}_{jmt} + \tau^{pA}_{Mt} + \mu^{pA}_{jmt} \tag{3}$$

$$p^{H}_{jmt} = \delta_{2j} x^{H}_{jmt} + \delta_{3j} p^{H}_{jmt-12} + \tau^{pH}_{Mt} + \mu^{pH}_{jmt} \tag{4}$$

where x^{A}_{jmt} and x^{H}_{jmt} are the room attributes for Airbnb and hotels. τ^{pA}_{Mt} and τ^{pH}_{Mt} are market-specific seasonality fixed effects, which capture unobserved demand shocks that are associated with time of the year and that drive both prices and demand. The error terms are allowed to be correlated with ϵ^{1}_{ijmt}. The hotel price during the same time the previous year p_{jmt-12} serves as an instrumental variable for hotel prices, and it captures the underlying cost related to the time of year that is uncorrelated with current-period demand shocks. Hotel prices are highly seasonal within a year and comparable across years. The 12-month lagged unobservables and the current unobservables are unlikely to be serially correlated given the relatively long time gap. The seasonality fixed effects $\tau^{pH}_{mt}, \tau^{pA}_{mt}$ and product characteristics x^{A}_{jmt}, x^{H}_{jmt} are the observed choice characteristics that also affect the utility.

We run the regressions in Equations 2, 3, and 4 in the first stage of the estimation. Following Petrin and Train (2010), we run separate regressions for each choice j = 1, ..., 6 using all instruments in each equation. The regression results are in the appendix. The partial F-statistics for the instruments in the three equations are 104.1, 36.2, and 1942.5, respectively, suggesting that the instruments satisfy the relevance condition.[15] The R-squares of the Airbnb supply, Airbnb pricing, and hotel pricing equations are larger than 0.7, which suggests that the instruments and the choice characteristics used in these equations sufficiently

[15]For the hotel pricing equation, the R-squared of the unrestricted regression is 0.902, and the R-squared of the restricted regression is 0.785, leading to a partial F-statistic of 1942.5.

explain Airbnb and hotel supply-side conduct. This is not entirely surprising, however, as the hotel industry widely adopts automated pricing algorithms based on seasonal demand, and Airbnb hosts tend to follow the pricing strategies of hotels in their neighborhoods.

5 Estimation Methods

5.1 Derivation of the Error Term Structure

The error term structure is similar to that specified in Petrin and Train (2010) and Park and Gupta (2009). The nested logit error term ζ_{imt} is a standard normal error and is common across j. The idiosyncratic utility shock has two components, $\epsilon_{ijmt} = \epsilon^1_{ijmt} + \epsilon^2_{ijmt}$, where ϵ^1_{ijmt} is the correlated component that causes endogeneity and ϵ^2_{ijmt} is the uncorrelated component with an i.i.d. extreme value distribution. For hotel options $j = 1, 2, 3$, we specify ϵ^1_{ijmt} and the control function μ^{pH}_{jmt} to be joint normal and independent over j:

$$\begin{aligned}
\begin{pmatrix} \mu^{pH}_{jmt} \\ \epsilon^1_{ijmt} \end{pmatrix} &= \begin{pmatrix} a_{11,j} & 0 \\ a_{21,j} & a_{22,j} \end{pmatrix} \begin{bmatrix} w^H_{1ijmt} \\ w^H_{2ijmt} \end{bmatrix} \\
\mu^{pH}_{jmt} &= a_{11,j} w^H_{1ijmt} \\
\epsilon^1_{ijmt} &= a_{21,j} w^H_{1ijmt} + a_{22,j} w^H_{2ijmt}
\end{aligned} \tag{5}$$

where w^H_{1ijmt} and w^H_{2ijmt} are i.i.d. standard normal errors with means of 0 and standard deviations of 1. Similarly, for Airbnb options $j = 4, 5, 6$, we specify ϵ^1_{ijmt} and the control functions $\mu^n_{jmt}, \mu^{pA}_{jmt}$ to be joint normal and independent over j:

$$\begin{pmatrix} \mu^{pA}_{jmt} \\ \mu^n_{jmt} \\ \epsilon^1_{ijmt} \end{pmatrix} = \begin{pmatrix} b_{11,j} & 0 & 0 \\ b_{21,j} & b_{22,j} & 0 \\ b_{31,j} & b_{32,j} & b_{33,j} \end{pmatrix} \begin{bmatrix} w^A_{1ijmt} \\ w^A_{2ijmt} \\ w^A_{3ijmt} \end{bmatrix}$$

$$\begin{aligned}
\mu^{pA}_{jmt} &= b_{11,j} w^A_{1ijmt} \\
\mu^n_{jmt} &= b_{21,j} w^A_{1ijmt} + b_{22,j} w^A_{2ijmt} \\
\epsilon^1_{ijmt} &= b_{31,j} w^A_{1ijmt} + b_{32,j} w^A_{2ijmt} + b_{33,j} w^A_{3ijmt}
\end{aligned} \tag{6}$$

where w^A_{1ijmt}, w^A_{2ijmt} and w^A_{3ijmt} are i.i.d. standard normal errors with means of 0 and standard deviations of 1. Substituting Equations 5 and 6 into Equation 1, we can obtain the final model estimated in the second step:

$$\begin{aligned}
u^H_{ijmt} &= \theta_j + \beta^H_i x^H_{jmt} + \alpha_i p^H_{jmt} + \gamma_{0j} n^H_{jmt} + \tau_{iMt} + \beta_{T1} T_t + \beta_{T2} T_t^2 \\
&\quad + \sigma \zeta_{imt} + \lambda_{1j} \mu^{pH}_{jmt} + a_{22,j} w^H_{2ijmt} + \epsilon^2_{ijmt}, \qquad j = 1,2,3 \\
u^A_{ijmt} &= \theta_j + \theta^A_{ij} + \beta^A x^A_{jmt} + \alpha_i p^A_{jmt} + \gamma_{1j} n^A_{jmt} + \gamma_{2j} \left(n^A_{jmt}\right)^2 \\
&\quad + \tau_{iMt} + \beta_{T1} T_t + \beta_{T2} T_t^2 + \beta_{TA} T^A_{Mt} \\
&\quad + \sigma \zeta_{imt} + \lambda_{2j} \mu^{pA}_{jmt} + \lambda_{3j} \mu^n_{jmt} + b_{33,j} w^A_{3ijmt} + \epsilon^2_{ijmt}, \qquad j = 4,5,6 \\
u_{i0mt} &= \epsilon_{i0mt}
\end{aligned} \tag{7}$$

where $\lambda_{1j} = \frac{a_{21,j}}{a_{11,j}}$, $\lambda_{2j} = \frac{b_{31,j}}{b_{11,j}} - \frac{b_{32,j} b_{21,j}}{b_{22,j} b_{11,j}}$ and $\lambda_{3j} = \frac{b_{32,j}}{b_{22,j}}$. The parameters $\{\lambda_{1j}, \lambda_{2j}, \lambda_{3j}, a_{22,j}, b_{33,j}\}$ are estimated in the model.

5.2 Estimation Procedure

In the first step, we obtain the residuals $\left\{\hat{\mu}^n_{jmt}, \hat{\mu}^{pA}_{jmt}, \hat{\mu}^{pH}_{jmt},\right\}$ using Equations 2, 3, and 4. As in Petrin and Train (2010), we use all the instruments in each equation to run separate regressions for each choice $j = 1, ..., 6$. In the second step, we use maximum likelihood estimation (MLE) to estimate the model in Equation 7. To construct the likelihood function, we denote the deterministic part of the utility function as $V(\cdot)$. The choice probabilities take a mixed logit form, with the mixing over the distribution of the error components $\left\{w^H_{2ijmt}, w^A_{3ijmt}\right\}$ and the heterogeneity $\{\eta_i, \zeta_{imt}\}$:

$$\begin{aligned}
P_{jmt}\left(w^H_{2ijmt}, w^A_{3ijmt}\right) &= \int \frac{\exp\left(V_{ijmt}\left(\eta_i, \zeta_{imt}, w^H_{2ijmt}, w^A_{3ijmt}\right)\right)}{1 + \sum_k \exp\left(V_{ikmt}\left(\eta_i, \zeta_{imt}, w^H_{2ikmt}, w^A_{3ikmt}\right)\right)} \varphi(\eta_i) \varphi(\zeta_{imt})\, d\eta_i d\zeta_{imt} \\
P_{jmt} &= \int P_{jmt}\left(w^H_{2ijmt}, w^A_{3ijmt}\right) \varphi\left(w^H_{2ijmt}\right) \varphi\left(w^A_{3ijmt}\right) dw^H_{2ijmt} dw^A_{3ijmt}
\end{aligned}$$

where $\eta_i \equiv \{\eta_i^{conv}, \eta_i^{spa}\}$. The integral is approximated through simulation. We first draw a set of product- and time-specific shocks for each tract $\left\{w^H_{2ijmt}\right\}_{j=1,2,3}, \left\{w^A_{3ijmt}\right\}_{j=4,5,6}$ and a set of individual-specific shocks $\{\eta_i, \zeta_{imt}\}$ from their standard normal densities. We calculate the logit formula above for this draw, repeat the process for numerous draws and average the results. To increase accuracy, we use a large number of Halton (1960) draws instead of independent random draws. Let P_{ijmt} denote the choice probability for segment i. The likelihood function is

$$L = \sum_{t=2008}^{t=2012} \sum_{m} \sum_{j=0}^{3} q_{jmt} \log \left(\sum_{i} P_{ijmt} \lambda_{iM} \right) + \sum_{t=2014}^{t=2015} \sum_{m} \sum_{j=0}^{6} q_{jmt} \log \left(\sum_{i} P_{ijmt} \lambda_{iM} \right)$$

where q_{jmt} is the observed demand for product j in tract m at time t.

We incorporate additional aggregate data to help identify consumer heterogeneity by matching the percent of Airbnb sales that comes from business travelers (10%).[16] As discussed later in the estimation result section, we identify two segments which can be mapped to business and leisure travelers in practice. We first estimate the model without the aggregate data on business travelers and obtain the "labels" of each segment (i.e., segment 1 corresponds to business travelers). We then impose the aggregate data restriction and conduct the full estimation. In particular, let B denote the observed percentage of sales that comes from business travelers for all cities and let $\hat{B}(\Theta) \equiv \frac{\sum_{t=2014}^{t=2015} \sum_m \sum_{j=3}^{6} M_m P_{jmt}^B \lambda_M^B}{\sum_{t=2014}^{t=2015} \sum_m \sum_{j=3}^{6} M_m \left(\sum_i P_{ijmt} \lambda_{iM} \right)}$ denote the predicted percentage, where Θ is the set of model parameters, M_m is the potential market size, P_{jmt}^B is the choice probability of business travelers, and λ_M^B is the fraction of business travelers. We solve a constrained maximization problem in which the aggregate data serve as an over-identifying restriction ($\hat{B}(\Theta) = B$) when maximizing the likelihood above.

5.3 Identification

The main goal of identification is to recover the underlying seasonality from the observed one. The market-specific underlying seasonality τ_{iMt} and consumer composition λ_{iM} are mainly identified from multi-year panel hotel data from the pre-Airbnb period, as 15-month Airbnb data are not sufficient to identify these market-specific variables. We assume that

[16]See https://www.bloomberg.com/news/articles/2015-07-20/airbnb-overhauls-service-for-business-travele

τ_{iMt} and λ_{iM} do not change before and after Airbnb entry.

Given τ_{iMt}, or the underlying market size, we can calculate the market expansion effect in the post-Airbnb period. The increase in total industry sales could come from both exogenous economic change and Airbnb's market expansion effect, which presents a challenge. During our sample period, the economy recovers from the financial crisis in 2008 and potentially causes an increase in industry sales for all cities. Meanwhile, the growth of Airbnb in these cities also expands the market and generates additional industry sales. These two forces must be distinguished to identify the market expansion effect of Airbnb. We assume that the cities share the same economic trend, as travelers are coming from all over the United States. Using time fixed effects to control for the economic trend, the correlation between Airbnb's presence and the total demand increase across markets identifies the market expansion from Airbnb. The identification of market expansion mainly comes from cross-market variations in Airbnb's presence and sales.

6 Estimation Results

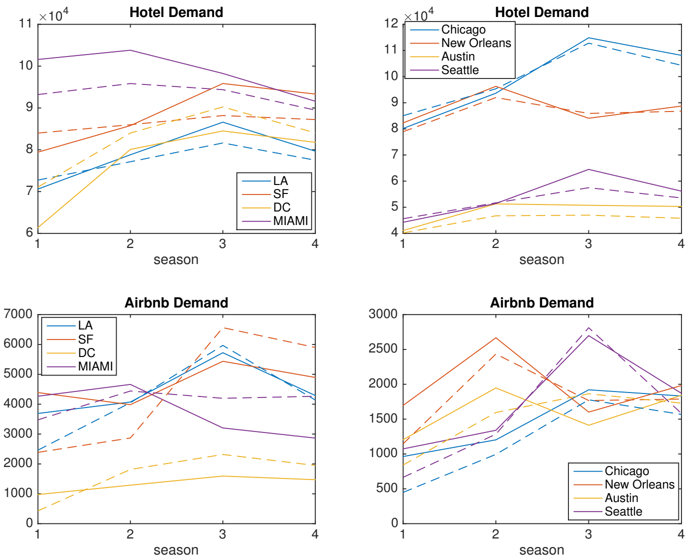
6.1 Model Fit

Figure 5 presents the observed and predicted hotel and Airbnb sales by season, by city and over time. The model is capable of fitting the seasonal demand patterns across cities and the overall time trend. The predicted fraction of leisure travelers among Airbnb consumers (89.8%) fits the observed fraction (90%). Finally, the estimated fraction of leisure travelers within industry-wide underlying demand (82.8%) is comparable to the observed fraction (79%) in industry reports (U.S. Travel Association 2015), which serves as an out-of-sample validation.[17] Overall, these results suggest that the model can recover the values of hotel and Airbnb options across cities, across consumer types, and over time.

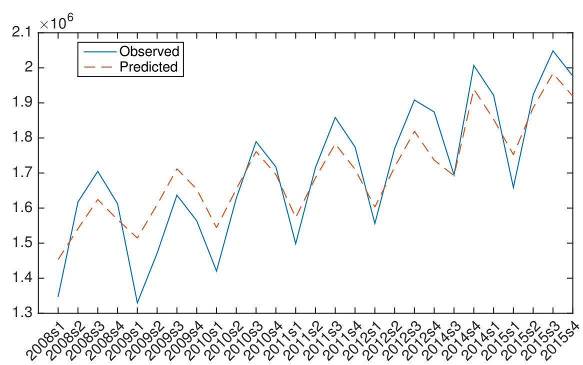
[17] See https://www.ustravel.org/answersheet.

Figure 5: Model Fit

(a) Hotel and Airbnb Demand



(b) Hotel Demand over Time



Notes: Solid lines represent observed values and dashed lines represent predicted values in Subfigure (a).

6.2 Parameter Estimates

The data identify two heterogeneous unobserved types.[18] Segment 1 consumers are much less price sensitive than Segment 2 consumers. Segment 1 consumers care more about convention spaces and value ski/spa/golf/boutique facilities positively. Segment 2 consumers value ski/spa/golf/boutique facilities negatively, suggesting that they are budget-minded travelers

[18]We also estimate another specification with three consumer types. The original specification outperforms this specification under the Akaike information criterion (AIC) and Bayesian information criterion (BIC). We thus keep the original specification.

who are unwilling to pay for luxury facilities. Segment 1 shares preferences similar to those of business travelers and Segment 2 shares preferences similar to those of leisure travelers in practice, so we refer to them as business and leisure travelers from this point forward. We find that business travelers have a lower valuation for staying in Airbnb rooms than leisure travelers do, especially for entire homes/apartments that are not hotel comparable. The product fixed effects of Airbnb for business travelers are negative and significant, which is consistent with the industry discussion regarding business travelers potentially finding Airbnb stays inconvenient. Business travelers might feel uncomfortable sharing a room with their host and may also require certain facilities to work during their stay. This may have motivated Airbnb's "Business Traveler Ready" program that started in July 2015.[19]

The distinction between for-business and not-for-business rooms in practice suggests that business travelers may only value Airbnb listings that are "Business Traveler Ready". Therefore, only for-business rooms should be counted towards Segment 1's n^A_{jmt} in the model estimation. To more accurately capture business and leisure travelers' preference in this context, we adopt Airbnb's definition of "Business Travel Ready" rooms and classify rooms into two groups: rooms that are suitable for business travelers ("for-business rooms") and rooms that are not.[20] We re-run the estimation and let n^A_{jmt} take the value of for-business rooms if $i = 1$ and all rooms if $i = 2$. The estimates from the new specification (Table 4 below) are very robust compared to those from the original specification (Table 12 in the appendix). Given that the new specification can more precisely capture consumer choice decisions in this context, we use the new model specification as the main specification. The rest of the analyses in this paper are based on the new estimates.

We find that the two types share similar demand elasticity patterns across room types,

[19] See, for instance, `https://www.bloomberg.com/news/articles/2015-07-20/airbnb-overhauls-service-for-business-travelers` and `https://skift.com/2015/11/16/understanding-how-airbnb-empowers-hosts-with-new-business-travel-strategy/`.

[20] "Business Travel Ready" rooms are those 1) where hosts respond to potential guests within 24 hours, and that 2) have a cleanliness rating, a location rating, and a check-in process rating of 4.5 or above; 3) do not allow pets; 4) do not allow smoking; 5) have Internet access, a washer, and a dryer; and 6) include the entire home or apartment.

as shown in Table 3: both types are more price elastic to high-end hotels than to low-end hotels, and they are more price elastic to hotel-comparable entire homes than to private rooms. However, the two types have important differences in their propensity to travel, or the underlying seasonality, which is captured by the estimated market-season fixed effects τ_{iMt}. Intuitively, business travel is associated with business activities, which may occur over the course of the year, so the propensity to travel remains stable over time; leisure travel is closely linked to destination weather and vacation schedules, so the propensity to travel may fluctuate across seasons and markets. Consistent with our intuition, we find that segment 1 consumers, whose seasonality fixed effects τ_{iMt} are normalized to zero, correspond to business travelers and Segment 2 consumers, whose τ_{iMt} are estimated and found to vary over time, correspond to leisure travelers.

We compare the estimated market-season fixed effects τ_{iMt} (i.e., underlying seasonal demand) with the observed demand in Figure 6. The y-axis on the left represents the observed demand and the y-axis on the right represents τ_{iMt}. There are eight cities and four seasonality fixed effects for each city. We find that the underlying demand (dashed lines) follows seasonality patterns similar to those for observed demand (solid lines). However, the underlying demand is more volatile and higher during high-demand seasons, suggesting that the realized demand could have been higher during those times. For instance, the underlying demand in San Francisco and Seattle is higher than the observed demand in summer and fall. This finding validates our concern that hotel seasonal pricing has a dampening effect on demand and echoes the importance of distinguishing between underlying and observed seasonality. Einav (2007) obtains similar findings that the underlying demand and the observed demand at the box office differ in the movie industry.

Table 4 presents the remaining parameter estimates in the choice utility. The estimates of segment sizes show that, on average, 82.8% of travelers are leisure travelers. New Orleans has the largest fraction of leisure travelers (91.0%), while San Francisco has the smallest fraction of leisure travelers (73.8%). We find that consumers value hotels and Airbnb avail-

Table 3: Demand Elasticities

	Hotel			Airbnb		
	H1	H2	H3	A1	A2	A3
Segment 1: Business	-0.0181	-0.0142	-0.0105	-0.0309	-0.0189	na
Segment2: Leisure	-2.5942	-1.8959	-1.2317	-3.0876	-1.9190	-1.0252

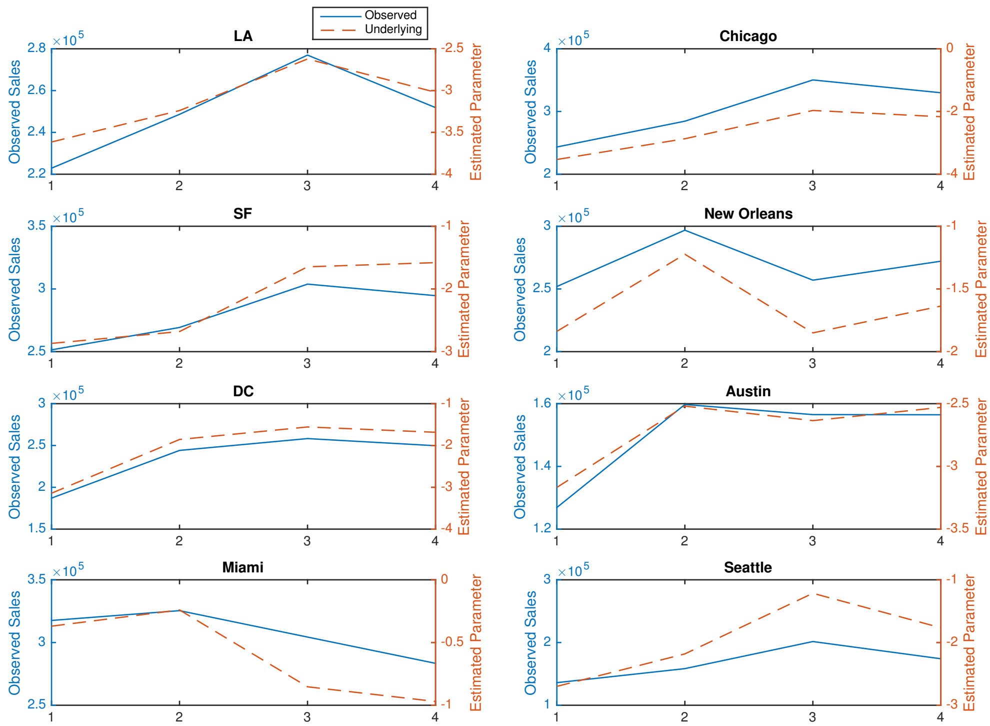
Notes: "H1, H2, and H3" represent high-end, mid-range, and low-end hotels, respectively. "A1, A2, and A3" represent an entire home/apartment that is not hotel comparable, an entire home/apartment that is hotel comparable, and a private room, respectively.

Table 4: Parameter Estimates

		Est	Std			Est	Std
Product FE θ_j	H1	-1.575**	0.0077	Price $\bar{\alpha}_i$	Business	-0.000142**	4.432e-6
	H2	-1.138**	0.0248		Leisure	-0.0142**	2.603e-4
	H3	-2.001**	0.0209	Convention Space $\bar{\beta}_i^{conv}$	Business	1.984**	0.0069
Product FE θ_j	A1	0.698**	0.0588		Leisure	1.258**	0.0109
	A2	-0.314**	0.0194	Std σ^{conv}		0.0666**	0.0038
	A3	-0.957**	0.0491	Ski/Spa/Golf/Boutique $\bar{\beta}_i^{spa}$	Business	0.648**	0.0198
Product FE:	A1	-4.531**	0.0552		Leisure	-1.810**	0.0214
Airbnb θ_{ij}^A	A2	-3.532**	0.0561	Std σ^{spa}		0.0413**	0.0010
# of Hotels γ_{0j}	H1	2.936**	0.0145	Restaurant β^H		-0.220**	0.0019
(in hundreds)	H2	1.396**	0.0194	All Suites		0.110**	0.0472
	H3	2.139**	0.0184	# of Bedrooms		0.444**	0.0359
# of Airbnb γ_{1j}	A1	6.995**	0.0657	# of Bathrooms		-0.514**	0.0877
(in thousands)	A2	4.799**	0.0812	Overall Rating		-1.957	1.210
	A3	3.645**	0.0708	# of Reviews		0.0371*	0.0173
# of Airbnb:	A1	-2.588**	0.0469	Heating β^A		1.998**	0.0735
Quadratic γ_{2j}	A2	-1.482**	0.0596	Kitchen		2.194**	0.0420
(in thousands)	A3	-1.417**	0.1667	Dryer		0.124	0.0687
Residual:	H1	3.336**	0.0043	Doorman		-1.914**	0.0957
Hotel Price λ_{1j}	H2	2.291**	0.0216	Intercom		0.316**	0.0807
	H3	4.488**	0.0042		Los Angeles	0.831**	0.0413
Residual:	A1	0.666**	0.0546		San Francisco	0.738**	0.0421
Airbnb Price λ_{2j}	A2	0.876**	0.0382		D.C.	0.768**	0.0079
	A3	0.250**	0.0893	Fraction of Leisure $\gamma_{i=2,M}$	Miami	0.824**	0.0413
Residual:	A1	0.185**	0.0653		Chicago	0.866**	0.0891
Airbnb Supply λ_{3j}	A2	-0.0881	0.0876		Austin	0.823**	0.0704
	A3	0.0434*	0.0207		New Orleans	0.910**	0.0117
Time Trend: β_{T1}		0.0524	0.0318		Seattle	0.861**	0.0350
Time Trend: Quadratic β_{T2}		0.0058*	0.0027				
Time Trend: Airbnb β_{TA}		0.1363**	0.0396	Nested Logit σ		0.0010**	2.906e-5

Notes: * and ** represent significance at the 5% and 1% levels. "H1, H2, and H3" represent high-end, mid-range, and low-end hotels, respectively. "A1, A2, and A3" represent an entire home/apartment that is not hotel comparable, an entire home/apartment that is hotel comparable, and a private room, respectively.

Figure 6: Parameter Estimates: Underlying Seasonal FEs (τ_{iMt}) and Observed Seasonality



Notes: The x-axis represents the four seasons: winter (Nov–Jan), spring (Feb–May), summer (Jun–Aug), and fall (Sep–Oct). The y-axis on the left represents observed demand and the y-axis on the right represents estimated seasonality fixed effects.

ability positively. The coefficients on the quadratic terms of Airbnb availability are negative, suggesting that the marginal utility from additional listings is diminishing.[21] The coefficients on the control function residuals are all significant, suggesting the importance of addressing the endogeneity issue. A positive (negative) coefficient occurs when the endogenous variable is larger (smaller) than can be explained by the observed factors (Petrin and Train 2010). The positive coefficients on hotel prices, Airbnb prices and supply indicate that there are unobserved favorable factors that drive up both demand and prices/supply. The nested logit coefficient σ is significantly different from one. It implies a strong substitution between the outside and inside good and, in turn, a strong market expansion effect, as is discovered in

[21]To make the variable values comparable in magnitude in the estimation, we scale down the number of hotels and Airbnb listings so that the number of hotels is in the hundreds and the number of Airbnb listings is in the thousands. Although the quadratic coefficient is negative, the number of Airbnb listings does not reach the point where more listings lead to lower utility.

the next subsection. Finally, the coefficient for the number of months since Airbnb reached a significant presence is positive and significant, which suggests that Airbnb's history in a specific city is important, as it allows for broader awareness and acceptance of this sharing economy platform.

6.3 Analysis of Results

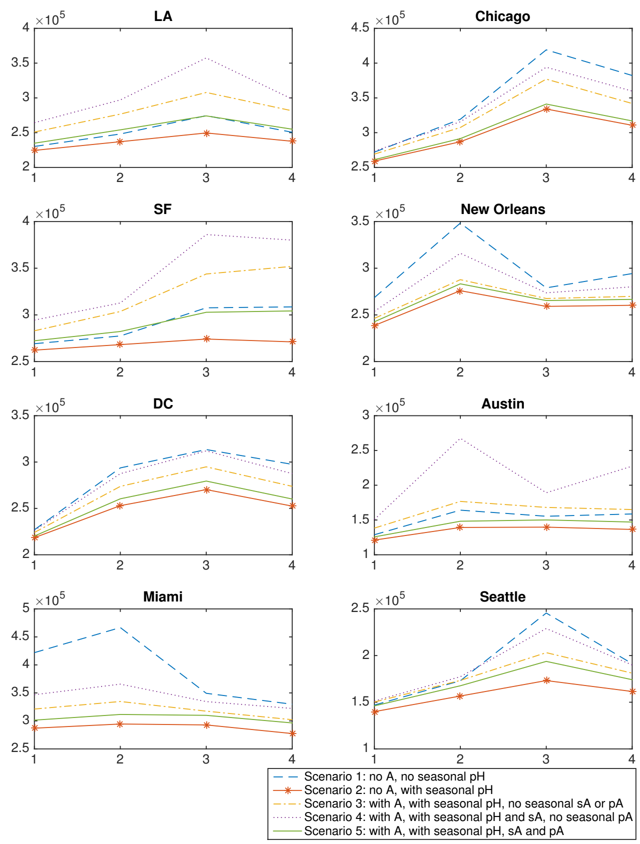
We use the estimated demand system to study the impact of Airbnb on the travel industry given observed prices and supply. In particular, we study how it affects the industry's ability to accommodate seasonal demand and how it cannibalizes or expands existing demand. We simulate the demand under alternative scenarios and compare the market outcome under each scenario. Note that the purpose of these analyses is to *decompose* the overall Airbnb effect into different effects (i.e., amplifying and dampening effects; cannibalization and market expansion effects) in the current market; the analyses are based on the observed supply-side strategies. This is different from the supply-side counterfactuals in the next section, in which the analyses are based on the optimal supply-side strategies solved in equilibrium.

6.3.1 Amplifying and Dampening Effects of Seasonal Firm Conduct

A key impact of Airbnb on the industry is the existence of alternative approaches to accommodating seasonal demand. While hotel seasonal pricing dampens underlying demand by raising prices during high-demand seasons, Airbnb's seasonal supply amplifies underlying demand by offering more rooms during high-demand seasons. Meanwhile, Airbnb's seasonal pricing has a dampening effect similar to that of hotel seasonal pricing, so the net impact is empirically ambiguous.

To quantify the dampening and amplifying effects of firms' seasonal conduct, we simulate the demand under the following counterfactual scenarios: 1) there is no Airbnb, and hotel prices are fixed at the low-demand season level ("non-seasonal"); 2) there is no Airbnb, and

Figure 7: Dampening Effect and Amplifying Effect



hotels prices are seasonal as observed; 3) Airbnb enters with non-seasonal supply and non-seasonal pricing, and hotel prices are seasonal; 4) Airbnb enters with seasonal supply and non-seasonal pricing, and hotel prices are seasonal; and 5) all firms' conduct—Airbnb supply and pricing and hotel pricing—is seasonal. Scenario 1 represents the underlying demand that can be realized given hotel offerings without seasonal pricing. The difference between Scenarios 1 and 2 illustrates the dampening effect of hotel seasonal pricing. The difference between Scenarios 2 and 3 illustrates the effect of Airbnb's non-seasonal presence. The difference between Scenarios 3 and 4 illustrates the amplifying effect of Airbnb's seasonal supply. The difference between Scenarios 4 and 5 illustrates the dampening effect of Airbnb's seasonal pricing.

We plot the simulated season-tract level demand in Figure 7. The five lines represent the demand under the five scenarios, and the gaps between the five lines represent the corresponding dampening or amplifying effects. In general, we find that the demand under Scenario 1 is the highest. Allowing for hotel seasonal pricing substantially reduces demand, as in Scenario 2. Introducing Airbnb and adding Airbnb seasonal supply increases demand as in Scenarios 3 and 4, so that Airbnb allows the industry to accommodate more demand. In cities with a strong Airbnb presence (e.g., Los Angeles and San Francisco), the realized demand is even higher than that in Scenario 1, suggesting that Airbnb is able to stimulate additional underlying demand. Finally, adding Airbnb's seasonal pricing limits this effect and causes a demand reduction similar to that of hotel seasonal pricing, as in Scenario 5. In all the cities, the effects are greater during the high-demand seasons.

Overall, we find that hotels' seasonal pricing (i.e., higher prices during high-demand seasons) dampens the underlying demand by 13.7%, on average, with a maximum reduction of 26.1% in Miami. Airbnb's non-seasonal presence (i.e., both supply and pricing are non-seasonal) can help recover some of that loss. Adding Airbnb's seasonal supply (i.e., more listings during high-demand seasons) can further help recover 67.5% of that loss (or even stimulate more demand in some cities), suggesting a strong amplifying effect. However, with Airbnb seasonal pricing, only 34.3% of that loss is recovered. Overall, Airbnb still helps resolve the tension between cyclical demand and fixed hotel capacity so that the industry can better meet the seasonal demand. This positive effect is particularly large in cities where Airbnb has a large presence and people are more aware of it, such as Los Angeles, San Francisco, and Austin.

6.3.2 Cannibalization and Market Expansion

To evaluate the impact of Airbnb on hotels, we simulate hotel sales without Airbnb for the post-Airbnb period, which we denote as D^{H0}. Let D^{H1} denote the observed hotel sales with Airbnb, and let D^{A} denote Airbnb sales. Cannibalization is defined as the hotel sales that could have been realized in the absence of Airbnb, or $D^{H0} - D^{H1}$. Market expansion is

Table 5: Cannibalization: Consumer Heterogeneity

	% Change in Hotel Sales			% of Airbnb Sales from Cannibalization		
	H1	H2	H3	Mean	Min	Max
Business	-0.267	-0.258	-0.270	70.9	61.9	78.7
Leisure	-0.847	-0.862	-0.865	4.7	1.0	14.9
Overall	-0.299	-0.398	-0.500	9.0	1.7	36.3

Notes: "H1, H2, and H3" represent high-end, mid-range, and low-end hotels, respectively. The second column shows the summary statistics for the cannibalization rate across markets by consumer type.

defined as the additional sales that Airbnb has created, or $D^A - \left(D^{H0} - D^{H1}\right)$. We focus on two cannibalization effect measures: the percentage change in hotel sales ($\frac{D^{H1}-D^{H0}}{D^{H0}}$) and the percentage of Airbnb sales that comes from cannibalization ($\frac{D^{H0}-D^{H1}}{D^A}$). The results are presented in Table 5.

We find that Airbnb causes a mild reduction in hotel sales. The overall percentage change in hotel sales is between -0.30% and -0.50%. In terms of consumer types, leisure travelers generate a 3.2 times greater reduction in hotel sales than business travelers. However, they also have a larger market expansion effect; most leisure travelers' Airbnb consumption comes from market expansion, while most business travelers' Airbnb consumption comes from cannibalizing hotels. Therefore, although leisure travelers might hurt the hotels more, they are more beneficial to the industry. In terms of hotel types, leisure travelers account for 6.4% of high-end hotel sales and 38.3% of low-end hotel sales. Consequently, low-end hotels experience the largest sales reduction. In terms of seasons, the cannibalization effect increases significantly in high-demand seasons for low-end and mid-range hotels, while it remains relatively stable for high-end hotels throughout the year. This might be because low-end and mid-range hotels compete head-to-head with Airbnb for leisure travelers, especially during high-demand seasons when more Airbnb listings are available. High-end hotels attract more business travelers, and they are thus less affected.

In terms of cannibalization effects across cities, an important finding is that the magnitudes can be related to market-specific attributes such as seasonality, hotel prices and quality, and consumer composition. We find suggestive evidence that cannibalization can be stronger in cities where 1) demand is more seasonal, 2) high-end hotel prices are lower, 3) the quality of low-end hotels is lower, or 4) the fraction of leisure travelers is higher. The logic behind this result is that Airbnb is a closer substitute for low-end and less expensive hotels and is more attractive to leisure travelers. Cities with more seasonal demand are more likely to have a higher fraction of leisure travelers, and cities with lower high-end hotel prices or lower low-end hotel quality are more likely to have consumers who switch to Airbnb. In the appendix, we provide more details on how city attributes and consumer composition are related to the sizes of the cannibalization effect across cities.

In fact, we can use pre-Airbnb seasonality patterns and hotel attributes to predict whether and how much hotels will be damaged even before Airbnb enters a city. Cities with weaker seasonality of demand, more expensive high-end hotels, and higher-quality low-end hotels might not need to be overly concerned about the impact of Airbnb. Airbnb in such cities may be generating market expansion rather than cannibalizing hotel sales.

7 Supply-side Counterfactuals

The previous section presents the impact of Airbnb given the observed pricing and Airbnb supply. The observed hotel pricing, or the conventional wisdom of seasonal pricing, is built on the fixed-capacity constraint: hotels have fewer rooms left during high-demand seasons, so they raise their prices during those times. However, Airbnb's flexible capacity eliminates the scarcity of rooms in high-demand seasons. Airbnb also makes consumers more price elastic to hotels overall. It suggests that Airbnb has potentially changed the competitive landscape in this industry. Hotels need to re-optimize their pricing to respond to the changes.

We estimate the demand model without assuming that the observed prices are optimal and use the control function approach to treat the endogeneity issue. In the supply-side problem, we obtain the marginal cost of different hotel types from industry reports and use them to calculate optimal hotel pricing in equilibrium, which can be different from the observed pricing in practice. For Airbnb pricing and supply, we assume that the observed Airbnb prices are optimally determined by accounting for hotel prices, room types and characteristics. Given the prices, we assume that the observed Airbnb supply is optimally determined by individual hosts (choosing to list their properties if the prices exceed their variable costs). We use these assumptions to impute Airbnb variable costs. The rationale behind the Airbnb assumptions are later detailed in the model setup.

We do not assume that the hotel prices in the data are optimal because, despite the rapid growth of Airbnb, hotels do not appear to have fully responded in a fundamental way in practice. For instance, the CEO of Hyatt stated in an interview that he saw "no need for a direct business response to Airbnb, in part because it is offering a fundamentally different product than his branded hotels".[22] Furthermore, hotels widely adopt revenue-management-based pricing algorithms, which have been developed and used over the past few decades and have not yet been adapted to the presence of Airbnb in recent years.[23] To further examine whether hotel pricing has significantly responded to Airbnb during our sample period, we follow the approach of Zervas et al. (2017) and compare the difference between year-over-year hotel price changes for peak seasons and those for off-peak seasons. Airbnb's flexible supply can limit hotels' pricing power, especially during peak seasons, when the Airbnb supply is larger; thus. hotel prices are more likely to be affected during peak seasons than during off-peak seasons. If the observed difference between peak and off-peak prices shrinks as Airbnb grows over time, it may suggest that hotel pricing has been limited by Airbnb. For each city, we define the one season (or two seasons if the seasonality in that city exhibits two peaks such as New Orleans) with the largest observed demand as the "peak" season and define the other seasons as the "off-peak" season. We calculate $\Delta P_{jmt} = \left(p_{jmt}^{peak} - p_{jmt}^{off-peak}\right) - \left(p_{jmt-1}^{peak} - p_{jmt-1}^{off-peak}\right)$ for each pair of adjacent years and find

[22]See `https://www.globalrealestateexperts.com/2015/09/how-are-hotels-responding-to-airbnb-types/`.
[23]For a history of revenue management in the hotel industry, see `https://www.hvs.com/article/7733/an-hvs-guide-to-hotel-revenue-management/`.

that ΔP_{jmt} is close to zero over time for cities in our data sample. Therefore, we do not find evidence that the observed hotel pricing has significantly responded to Airbnb. The equilibrium analysis in this section allows us to illustrate whether and how hotel pricing should respond to the presence of Airbnb.

We use the demand estimates to solve for the optimal pricing problem for hotels in an equilibrium where hotel prices, Airbnb prices, and Airbnb supply are endogenous. To perform the analysis, we obtain hotel marginal cost data from industry reports and estimate the Airbnb host cost from the observed Airbnb supply. We explore the optimal hotel pricing strategy by hotel type and across markets, and conduct counterfactual analysis such as allowing Airbnb to behave like hotels and changing Airbnb host costs.

7.1 Supply-side Problem Setup

Hotel Pricing

Define the time period as a month. Every period, hotels of each type choose optimal prices by solving a profit maximization problem in a Bertrand-Nash equilibrium given Airbnb supply $\vec{n}^A_{mt} \equiv \left\{n^A_{jmt}\right\}_j$ and Airbnb prices $\vec{p}^A_{mt} \equiv \left\{p^A_{jmt}\right\}_j$:

$$\max_{p_{jmt}} \left(p^H_{jmt} - c_{jm}\right) M_m s^H_{jmt} \left(\vec{p}^H_{mt}, \vec{n}^A_{mt}, \vec{p}^A_{mt}\right)$$

where $\vec{p}^H_{mt} \equiv \left\{p^H_{jmt}\right\}_j$ and M_m is the potential market size. The market share of hotel type j in market m at time t equals $s^H_{jmt} = \sum_i \lambda_{iM} P_{ijmt}\left(\vec{p}^H_{mt}, \vec{n}^A_{mt}, \vec{p}^A_{mt}\right)$. The marginal costs c_{jm} come from industry reports. We do not allow marginal costs to vary over time, as the main driver of price variation over time in the hotel industry is demand variation over time.[24]

[24]Hotels account for the following factors when setting prices: location, demand, room type, and competition (`https://www.usatoday.com/story/travel/hotels/2014/10/26/how-hotels-come-up-with-rates/17792537/`). Among these, demand is the main time-varying factor. We allow marginal costs to differ by location/market and room type. The equilibrium analysis accounts for time-varying competition and demand.

Robustness checks show that the optimal pricing strategy that we find is robust to different levels of hotel marginal costs so that the results are not driven by the marginal cost values; the marginal costs affect the level of the optimal prices, but they do not affect the pricing patterns over time. The first-order condition of the above maximization problem is

$$M_m \left[\left(p^H_{jmt} - c_{jm} \right) \frac{\partial s^H_{jmt} \left(\vec{p}^H_{mt},\, \vec{n}^A_{mt},\, \vec{p}^A_{mt} \right)}{\partial p^H_{jmt}} + s^H_{jmt} \left(\vec{p}^H_{mt},\, \vec{n}^A_{mt},\, \vec{p}^A_{mt} \right) \right] = 0 \tag{8}$$

Airbnb Pricing

Unlike hotel prices, Airbnb prices are set in a highly decentralized way in practice. When setting prices, Airbnb hosts account for both "the intrinsic value of the property, location, and amenities" and seasonal demand and hotel prices.[25] This is also supported by the observed data patterns: Airbnb prices closely follow hotel prices over time; some Airbnb types are more comparable to particular hotel types than other Airbnb types. To parsimoniously capture this process, we empirically estimate how Airbnb prices are determined in the data by regressing the observed Airbnb prices of type l on the *observed* prices of the three types of hotels $\left\{ p^{H*}_{1mt}, p^{H*}_{2mt}, p^{H*}_{3mt} \right\}$ (capturing how Airbnb prices change with hotel prices and seasonal demand), the Airbnb room type fixed effects δ^p_l, and the Airbnb property characteristics x^p_{lmt} (capturing Airbnb and hotel price difference based on product differentiation):

$$\begin{aligned} p^{A*}_{lmt} &= \kappa^{Al}_1 p^{H*}_{1mt} + \kappa^{Al}_2 p^{H*}_{2mt} + \kappa^{Al}_3 p^{H*}_{3mt} + \delta^p_l + \gamma_x x^p_{lmt} + \varepsilon^p_{lmt} \\ &= \left(\sum_{j=1,2,3} \kappa^{Al}_j p^{H*}_{jmt} \right) + \hat{\Delta}^p_{lmt} \qquad l = 4,5,6 \end{aligned} \tag{9}$$

Let $\hat{\Delta}^P_{lmt}$ denote the fitted value of $\delta^p_l + \gamma_x x^p_{lmt} + \varepsilon^p_{lmt}$ that represents the portion of Airbnb prices that stems from "differentiation" or intrinsic quality. $\left\{ \kappa^{Al}_1, \kappa^{Al}_2, \kappa^{Al}_3 \right\}$ represent how

[25] See, for instance, `http://rentingyourplace.com/airbnb-101/pricing/`. Some hosts use third-party pricing services to price their listings (e.g. `https://beyondpricing.com/` and `https://www.everbooked.com/`). These services follow similar pricing logic and usually take the prices of hotels as benchmarks when setting their prices.

Table 6: Airbnb Pricing Estimation Results

DV: Airbnb Price		A1 ($l = 1$)		A2 ($l = 2$)		A3 ($l = 3$)	
		Est	Std	Est	Std	Est	Std
Hotel Price	H1 (κ_1^{Al})	0.408**	0.0604	0.0499	0.0381	0.0706**	0.0121
	H2 (κ_2^{Al})	0.287*	0.1277	0.440**	0.0822	0.176**	0.0260
	H3 (κ_3^{Al})	0.430**	0.1124	0.258**	0.0728	0.0419	0.0246
Airbnb Room Type FE δ_l^p		Yes		Yes		Yes	
Airbnb Room Characteristics x_{lmt}^p		Yes		Yes		Yes	
R-squared:		0.688		0.668		0.714	
N:		765		765		765	

Notes: * and ** represent significance at the 5% and 1% levels. "A1, A2, and A3" represent an entire home/apartment that is not hotel comparable, an entire home/apartment that is hotel comparable, and a private room, respectively. "H1, H2, and H3" represent high-end, mid-range, and low-end hotels, respectively.

the price of Airbnb room type l changes along with the prices of high-end, mid-range, and low-end hotels, respectively; different Airbnb room types can respond differently to prices of different hotels. Given the estimated coefficients on hotel prices $\left\{\kappa_1^{Al}, \kappa_2^{Al}, \kappa_3^{Al}\right\}$ (as shown in Table 6) and the fitted "differentiation" component $\hat{\Delta}_{lmt}^P$, we can generate new Airbnb prices given new hotel prices by substituting hotel prices from Equation 8 into the above equation. The implied assumption is that Airbnb hosts set prices *in the same way* in the counterfactuals as in the observed data. We believe that this assumption is reasonable because most Airbnb hosts are small mom-and-pop ventures that do not have the market power to affect the equilibrium. The assumption is that given alternative hotel prices, hosts account for the same factors when setting their prices. This approach allows Airbnb prices to flexibly change as hotel prices change, while at the same time accounting for the price differences due to product differentiation across room types and markets, which reflects how Airbnb prices are set in practice. This approach is more appealing than assuming that Airbnb also solves a room-type level optimization problem because Airbnb prices are set in a highly decentralized way in practice. We conduct robustness checks by varying the values of κ_j^{Al} in the counterfactuals and show in the appendix that the main supply-side findings remain qualitatively unaffected.

Airbnb Supply

Given Airbnb prices $\vec{p}^{A*}_{mt}$, Airbnb hosts choose to list their properties if the prices exceed their variable costs. We make this assumption for reasons similar to those discussed above. First, the size of the Airbnb market is still very small compared to that of hotels during our sample period; Airbnb accounts for less than 5% of the total available rooms even in major cities. Meanwhile, there are thousands of Airbnb hosts in each market. A single host's pricing decision is unlikely to affect the equilibrium pricing. We assume that the hosting cost on Airbnb for each host is drawn from a normal distribution. This variable cost of hosting, measured at the property level, can include both monetary cost and other costs that the hosts need to bear (e.g., the cost of cleaning by themselves if they operate on their own). The mean of the distribution varies by room type, by city, and over time:

$$c^A_{ijmt} = \bar{c}^A_{jmt} + \varepsilon^c_{ijmt} = \delta^c_j + \gamma_D D^c_m + \gamma_A \tau^A_t + \gamma_T T^A_{Mt} + \varepsilon^c_{ijmt} \tag{10}$$

where ε^c_{jmt} is i.i.d. normally distributed with mean 0 and variance $(\sigma^c)^2$. δ^c_j represents room type fixed effects. τ^A_t represents seasonality fixed effects, which capture time-varying hosting costs due to host availability; hosts may be more available during summer and less available during winter, when they are spending time with family and friends. T^A_{Mt} represents city-specific time trends and captures time-varying host costs across cities; hosts may be more receptive to the idea of a short-term rental on Airbnb in cities where Airbnb has a longer and stronger presence. D^c_m represents city-specific characteristics and contains tract-level demographics from the American Housing Survey and Airbnb regulation scores. Hosts with different age, income, education, marital status, with or without children, and employment status can have different costs of hosting. The cost of hosting also depends on whether there are any government regulations on Airbnb listings in a particular city.

We estimate the parameters of the distribution using the observed Airbnb supply data.

In particular, Airbnb hosts choose to list if $p^A_{jmt} > c^A_{ijmt}$ so that

$$n^A_{jmt} = N^A_{jm}\Phi\left(\frac{p^A_{jmt} - \bar{c}^A_{jmt}}{\sigma^c}\right) \tag{11}$$

where $\Phi(\cdot)$ is the cdf of the standard normal distribution. N^A_{jm} is the number of potential Airbnb properties in market m. We define potential Airbnb properties as properties that are either listed on Airbnb in the observed data or are rented out to locals. In particular, properties rented out to locals in the long-term rental market can potentially switch to listing on Airbnb for short-term rentals to tourists. The number of properties that are rented out to locals are collected from the American Housing Survey. Equation 11 can be re-written as

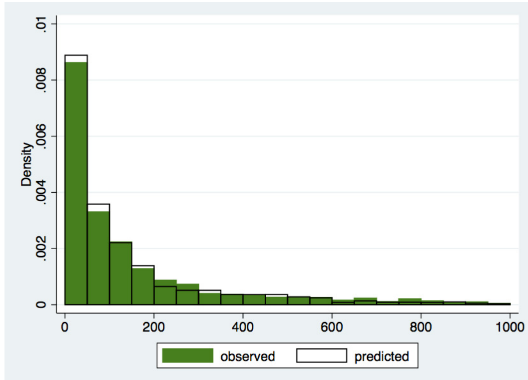
$$\begin{aligned}
\Phi^{-1}\left(\frac{n^A_{jmt}}{N^A_{jm}}\right) &= \frac{1}{\sigma^c}\left[p^A_{jmt} - \bar{c}^A_{jmt}\right] \\
&= \frac{1}{\sigma^c}p^A_{jmt} - \left[\frac{\delta^c_j}{\sigma^c} + \frac{\gamma_D}{\sigma^c}D^c_m + \frac{\gamma_A}{\sigma^c}\tau^A_t + \frac{\gamma_T}{\sigma^c}T^A_{Mt}\right] \\
&= \alpha^c p^A_{jmt} - \left[\tilde{\delta}^c_j + \tilde{\gamma}_D D^c_m + \tilde{\gamma}_A\tau^A_t + \tilde{\gamma}_T T^A_{Mt}\right]
\end{aligned}$$

where $\alpha^c = \frac{1}{\sigma^c}$. We are interested in obtaining the estimates of σ^c and $\bar{c}^A_{jmt}$ in order to calculate Airbnb supply in equilibrium using Equation 11. To empirically obtain these estimates from the data, we add an error term to the equation above and run the following regression:

$$\Phi^{-1}\left(\frac{n^A_{jmt}}{N^A_{jm}}\right) = \alpha^c p^A_{jmt} - \left[\tilde{\delta}^c_j + \tilde{\gamma}_D D^c_m + \tilde{\gamma}_A\tau^A_t + \tilde{\gamma}_T T^A_{Mt}\right] + \epsilon_{jmt} \tag{12}$$

We instrument p^A_{jmt} using hotel prices, as they are correlated with Airbnb prices but do not directly affect the cost of Airbnb hosts. The estimated coefficient α^c provides the estimate of $\sigma^c = \frac{1}{\alpha^c}$. Denote the fitted value of this regression $\hat{\Phi}^{-1}$. We can further obtain $\bar{c}^A_{jmt} = p^A_{jmt} - \sigma^c \cdot \hat{\Phi}^{-1}$.

Figure 8: Model Fit: Airbnb Supply



As shown in Figure 8, we are able to fit the observed Airbnb supply well using the method above. Table 7 presents the parameter estimates in Equation 12. The coefficients are mostly significant and all of them have the expected signs. The cost of hosting is the highest for listings that are not hotel comparable (i.e., larger properties) and is the lowest for private rooms. The cost is the highest in winter and lowest in summer. In terms of demographics, the cost of hosting is higher for hosts who are married, employed, and with children. It is lower for hosts with larger incomes or higher education, who can potentially outsource some of the management. In terms of government regulations, the cost of hosting is lower when there are favorable Airbnb regulations. Finally, the cost of hosting is decreasing over time at a slowing pace.

Using the estimated σ^c and $\bar{c}^A_{jmt}$, we can calculate the optimal Airbnb supply given the prices $\vec{p}^{A*}_{mt}$:

$$n^{A*}_{jmt} = N^A_{jm}\Phi\left(\frac{p^{A*}_{jmt} - \bar{c}^A_{jmt}}{\sigma^c}\right) \tag{13}$$

Equilibrium

The equilibrium is defined as the set of hotel prices, Airbnb prices and Airbnb supply $\left\{p^{H*}_{jmt}, p^{A*}_{jmt}, n^{A*}_{jmt}\right\}_j$ such that the conditions in Equation 8, 9, and 13 hold. Hotels choose the optimal prices to maximize their profits, given the optimal response of Airbnb; given hotel pricing, Airbnb pricing is determined, and Airbnb's potential hosts optimally choose to list

Table 7: Airbnb Cost Estimation Results

		Est	Std			Est	Std
Price (α^c)		0.00319**	0.000328	Demographics ($\tilde{\gamma}_D$)	Age	0.00915	0.00620
Product FE ($\tilde{\delta}_j^c$)	A2	-0.318**	0.0306		Income	-1.36e-6*	5.67e-7
	A3	-0.691**	0.0514		With kids	0.971*	0.316
Time Trend ($\tilde{\gamma}_T$)	Linear	-0.0227**	0.00470		Married	1.426**	0.225
	Quadratic	0.00114**	0.000363		Edu: bachelor	-1.086**	0.127
Seasonality ($\tilde{\gamma}_A$)	2: Spring	-0.0364*	0.0162		Work: labor force	1.637**	0.276
	3: Summer	-0.0698**	0.0165	Regulations ($\tilde{\gamma}_D$)	Framework	-0.0926**	0.00562
	4: Fall	-0.0517**	0.0165		Restrictions	-0.00895**	0.000972
					Licensing	-0.0924**	0.00999
N:	2,270	R-squared:	0.691		Enforcement	-0.0539**	0.00317

Notes: * and ** represent significance at the 5% and 1% levels. "A1, A2, and A3" represent an entire home/apartment that is not hotel comparable, an entire home/apartment that is hotel comparable, and a private room, respectively. "A1" and "Winter" serve as the baseline for product and seasonality fixed effect estimates. The variables on regulations are the scores of how friendly the policies are to Airbnb; the larger the scores, the friendlier the policies.

or not to list. The numerical algorithm to solve for the equilibrium is as follows:

(1) For each market m and time t, start with a guess of the optimal Airbnb supply $n_{jmt}^{A,k-1}$.

(2) Given the Airbnb supply, solve the hotels' first-order conditions in Equation 8 and obtain the optimal hotel prices $p_{jmt}^{H,k-1}$.

(3) Given the hotel prices, update the Airbnb supply $n_{jmt}^{A,k}$ using Equation 13.

(4) Check for the convergence of $\mid n_{jmt}^{A,k} - n_{jmt}^{A,k-1} \mid$ and $\mid p_{jmt}^{H,k} - p_{jmt}^{H,k-1} \mid$. If convergence is not achieved, return to step (2).

To solve for the equilibrium, we start with different initial guesses. The algorithm converges to the same solution, which suggests that our results are robust to different starting values of the algorithm.

7.2 Supply-side Result Analysis

7.2.1 Equilibrium Outcome

We first plot the optimal hotel pricing by hotel type and market over time in Figure 9. The solid lines represent observed hotel prices and the dashed lines represent optimal hotel prices. The conventional wisdom of hotel pricing is that hotels should conduct seasonal pricing by raising prices during high-demand seasons and reducing prices during low-demand seasons. Given the presence of Airbnb, we find that it is optimal for some hotel types in some cities to perform less seasonal pricing, or even counter-seasonal pricing. In particular, for Los Angeles, Chicago, and Seattle, **mid-range and low-end** hotels should exercise less seasonal pricing; for Miami and New Orleans, **high-end** hotels should exercise less seasonal pricing; for San Francisco, Washington D.C., and Austin, **all** hotel types should exercise less seasonal pricing.

7.2.2 Mechanism: Seasonal vs. Counter-Seasonal Pricing

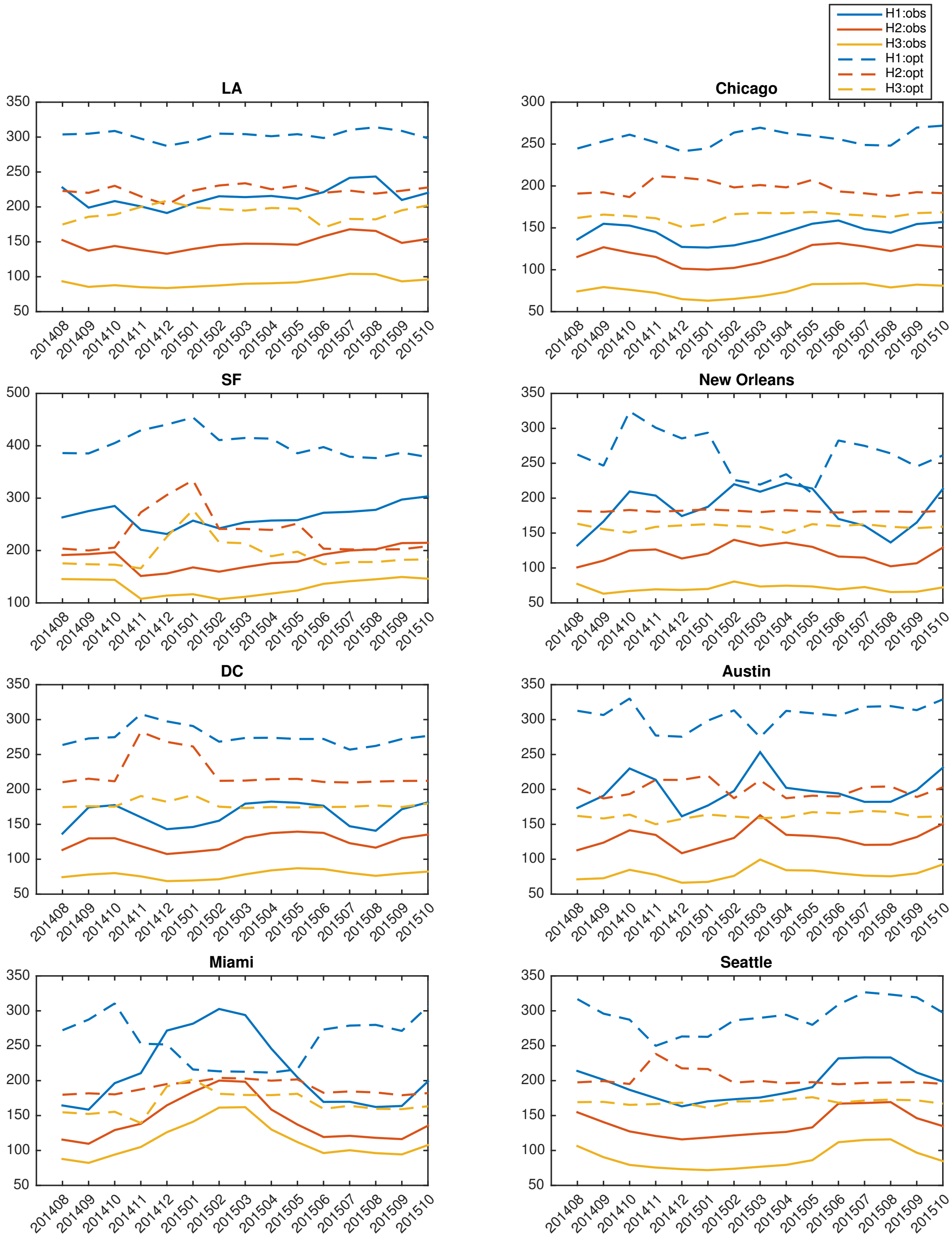
Why is it optimal for some hotel types and cities to conduct less seasonal pricing or even counter-seasonal pricing in the presence of Airbnb? The reason is that there are two forces in hotels' pricing decisions. Higher demand during peak seasons provides incentives to raise prices, yet it also drives up Airbnb supply and intensifies competition, which may reduce prices. Lower demand during off-peak seasons provides incentives to reduce prices, yet it also reduces Airbnb supply and softens competition, which may increase prices. Therefore, the prices in peak seasons can be higher or lower than those in off-peak seasons (i.e., seasonal or counter-seasonal pricing), depending on the net effect of the two forces.

These pricing incentives are summarized in the first-order conditions of hotel pricing. Accounting for the fact that Airbnb supply and prices are functions of hotel prices (i.e., n^{A*}_{lmt} is a function of p^{A*}_{lmt} and $p^{A*}_{lmt} = \hat{\Delta}^{p}_{jmt} + \sum_j \kappa^{Al}_{j} p^{H*}_{jmt}$ for each Airbnb type l), we can re-write Equation 8 as

$$p^{H*}_{jmt} = c_{jm} + \frac{1}{|\alpha| \left\{ 1 - \left[s^{H}_{jmt} + \sum_{l=4,5,6} \left(\kappa^{Al}_{j} - \frac{\gamma_{1j}}{|\alpha|} \frac{\partial n^{A}_{lmt}}{\partial p^{H}_{jmt}} \right) s^{A}_{lmt} \right] \right\}} \tag{14}$$

where α is the price coefficient and γ_{1j} is the coefficient of Airbnb supply in the consumer's choice utility. We keep the linear term of the number of Airbnb listings, $\gamma_{1j} n^{A}_{jmt}$, and drop the quadratic term, $\gamma_{2j} \left(n^{A}_{jmt} \right)^2$, in this derivation only for illustration purpose. The empirical

Figure 9: Optimal Hotel Pricing Strategy



equilibrium solution accounts for both terms as in the demand estimation. The critical term is

$$H \equiv s^H_{jmt} + \sum_{l=4,5,6} \left(\kappa^{Al}_j - \frac{\gamma_{1j}}{|\alpha|} \frac{\partial n^A_{lmt}}{\partial p^H_{jmt}} \right) s^A_{lmt}$$

In particular, when H is larger (smaller), the optimal hotel price is higher (lower).[26] H is larger when hotels' market share s^H_{jmt} is larger, Airbnb's market share $\left\{s^A_{lmt}\right\}_l$ is smaller (as $\kappa^{Al}_j - \frac{\gamma_{1j}}{|\alpha|} \frac{\partial n^A_{lmt}}{\partial p^H_{jmt}} < 0$, empirically), Airbnb's supply elasticity with respect to prices $\left\{\frac{\partial n^A_{lmt}}{\partial p^H_{jmt}}\right\}_l$ is smaller, and the "responsiveness" coefficients of Airbnb prices to hotel prices $\left\{\kappa^{Al}_j\right\}_l$ are larger. These components of H differ across hotel types and cities, so the optimal pricing strategy differs across hotel types and cities. To illustrate whether seasonal or counter-seasonal pricing is optimal for a particular hotel type in a particular city, we compare the values of H in peak and off-peak seasons; if H is larger (smaller) in peak seasons than in off-peak seasons, the optimal price is higher (lower) in the former than in the latter, which suggests seasonal pricing (counter-seasonal pricing). Let $\left\{H^{peak}_0, H^{off-peak}_0\right\}$ denote the value of H evaluated at the same price p in peak and off-peak seasons. Higher demand during peak seasons raises s^H_{jmt}, so that $H^{peak}_0 > H^{off-peak}_0$ may hold; the optimal price can be higher during peak seasons than during off-peak seasons (i.e., seasonal pricing). This incentive corresponds to the first force in the pricing decision: high demand motivates higher prices during peak seasons. However, higher demand during peak seasons also raises s^A_{lmt} and, if $\frac{\partial n^A_{lmt}}{\partial p^H_{jmt}}$ is large, reduces H so that $H^{peak}_0 < H^{off-peak}_0$ may hold; the optimal price may be lower during peak seasons than off-peak seasons (i.e., counter-seasonal pricing). This incentive corresponds to the second force in the pricing decision: high demand intensifies competition by inducing more Airbnb supply and reduces prices during peak seasons. The net effect of the two forces depends on how much higher demand raises s^H_{jmt} and s^A_{lmt} during peak seasons and how large $\frac{\partial n^A_{lmt}}{\partial p^H_{jmt}}$ is for the particular hotel type in the particular city. The

[26]This result comes from a simulation analysis of Equation 14. p^H_{jmt} appears on both sides of Equation 14. Holding $p^H_{jmt} = p$ the same, different cities and hotel types have different values of H. For each city and hotel type, let H^0 denote the value of H evaluated at the same price $p^H_{jmt} = p$. We solve for the optimal prices p^{H*}_{jmt} and find that higher H^0 is associated with higher p^{H*}_{jmt}.

second force dominates the first force when s^H_{jmt} is small, $\left\{s^A_{lmt}\right\}_l$ are large, and $\left\{\frac{\partial n^A_{lmt}}{\partial p^H_{jmt}}\right\}_l$ are large.[27]

The discussion above suggests that hotels should conduct less seasonal pricing or even counter-seasonal pricing in cities where their market share is smaller, Airbnb's market share is larger, and Airbnb's supply elasticity is larger. Market conditions that lead to one of these three conditions would lead to less seasonal pricing. On the hotel side, hotels' market share is smaller when there are higher hotel prices, lower hotel quality, and a higher fraction of leisure travelers. Cities with relatively more expansive high-end hotels (represented by a larger ratio of high-end to low-end hotel prices $p \equiv \frac{p^H}{p^L}$), lower quality high-end hotels (represented by a larger ratio of low-end to high-end hotel quality $l \equiv \frac{v^L}{v^H}$, where quality is measured as $x^{conv}_{jmt} + x^{spa}_{jmt}$), and a higher fraction of leisure travelers (γ_{iM}) are more likely to have high-end hotels conduct less seasonal pricing and low-end hotels conduct seasonal pricing. On the Airbnb side, Airbnb's market share is larger when there is a longer and stronger Airbnb presence. Airbnb's supply elasticity, $\frac{\partial n^{A*}_{lmt}}{\partial p^H_{jmt}} = \frac{1}{\sigma^c}\kappa^{Al}_j N^A_{lm}\phi\left(\frac{p^{A*}_{lmt} - \bar{c}^A_{lmt}}{\sigma^c}\right)$, is larger when there are larger total numbers of potential Airbnb properties (N^A_{lm}) and lower hosting costs ($\bar{c}^A_{lmt}$).[28] Hotels in these cities should conduct less seasonal pricing.

We find suggestive evidence that supports our predictions from the eight cities in our study. Table 8 tabulates market conditions, Airbnb supply elasticity, and hotel optimal pricing policies across cities (summarized from the results in Figure 9). The values in bold represent factors that induce less seasonal pricing based on our derivation. Consistent with the predictions, *low-end* hotels in Los Angeles, Chicago, and Seattle should conduct less

[27] This result can be derived from the model. To see how much higher underlying demand raises s^H_{jmt} during peak seasons, we calculate the elasticity of hotels' market share with respect to the seasonality fixed effects, $\frac{\partial s^H_{jmt}}{\partial \tau_{iMt}} = s^H_{jmt} s_{0mt}$, which is empirically larger when s^H_{jmt} is larger. The same logic applies to s^A_{lmt}.

[28] The average estimated hosting cost is larger than the observed price ($\bar{c}^A_{lmt} > p^A_{lmt}$) so that $\frac{1}{\sigma^c} N^A_{lm}\phi\left(\frac{p^A_{lmt} - \bar{c}^A_{lmt}}{\sigma^c}\right)$ is larger when $\bar{c}^A_{lmt}$ is smaller. The estimated hosting cost is larger than the observed price because the hosting cost $\bar{c}^A_{lmt}$ is identified from the fraction of Airbnb properties among all potential properties; the number of total potential properties N^A_{lm} (including those that are already listed on Airbnb and those that are rented out to locals in the housing market) is much larger than the observed number of Airbnb listings in the data.

Table 8: Hotel Pricing Strategy by City

	Hotel-side Market Conditions			Airbnb			Hotel		
	Price	Quality	% Leisure	supply elasticity			optimal pricing		
	$(p \equiv \frac{p^H}{p^L})$	$(l \equiv \frac{v^L}{v^H})$	(γ_{iM})	A1	A2	A3	H1	H2	H3
Los Angeles	2.33	0.012	83	2.77	2.30	**3.73**	+	–	–
San Francisco	2.12	0.014	74	3.26	3.36	**3.74**	–	–	–
D.C.	2.14	0.017	77	0.58	0.73	**1.22**	–	–	–
Miami	2.03	**0.056**	82	**2.72**	1.07	1.37	–	+	+
Chicago	2.07	0.020	87	0.48	0.50	**0.58**	+	–	–
New Orleans	2.01	0.001	82	0.87	1.08	**1.34**	–	+	+
Austin	**2.63**	0.001	**91**	1.44	1.36	**1.57**	–	–	–
Seattle	2.23	0.009	86	0.67	1.13	**1.88**	+	–	–

Notes: The results on hotel optimal pricing are summarized from Figure 9. "+" represents seasonal pricing (i.e., higher prices during high-demand seasons) and "–" represents less seasonal pricing or even counter-seasonal pricing (i.e., lower prices during high-demand seasons).

seasonal pricing, as Airbnb supply elasticities are relatively higher for low-end hotels than for high-end hotels. *High-end* hotels in Miami should exercise less seasonal pricing, as l is the largest across all cities and Airbnb supply elasticity is the largest for high-end hotels. *All* hotel types should conduct less seasonal pricing in Austin, San Francisco, and Washington D.C. High-end hotels should conduct less seasonal pricing in these cities because p and l are larger in San Francisco and Washington D.C., and p and γ_{iM} are the largest in Austin; low-end hotels should conduct less seasonal pricing as well because Airbnb supply elasticity is the largest for low-end hotels among the three hotel types in these cities.

7.3 Counterfactual Results

In this section, we study two counterfactual scenarios to explore how recent Airbnb and public policy changes can affect the competitive landscape in the travel industry. The first counterfactual varies the cost of Airbnb hosts from 80% to 130% of the current value, which is motivated by recent Airbnb and public policy changes that affect Airbnb hosts' costs. On the one hand, cities such as San Francisco and Los Angeles started to charge hotel taxes on Airbnb, which increases the costs of Airbnb hosts.[29] On the other hand, third-party services for Airbnb hosts such as room cleaning and key exchange services facilitate the hosting process, which can reduce the cost of hosting.[30] Although hosts need to pay for these services, as long as they voluntarily choose to use them, their hosting cost is likely to be lower. The recent trend of more "professional" hosts on Airbnb can also lead to lower costs of hosting per property due to specialization and economies of scale.[31] We explore how these changes can affect equilibrium hotel profits. The second counterfactual jointly varies Airbnb host costs and removes business travelers' lower valuation of Airbnb (i.e., let $\theta_{ij}^{A} = 0$), which is motivated by Airbnb's recent attempt to act more like hotels.[32] In the demand estimation, we find that business travelers have a lower valuation of Airbnb. In practice, Airbnb promotes their "Business Travel Ready" program and increases the provision of standardized services that are more comparable to those offered by hotels. We explore how this attempt can affect hotel profitability. In all these scenarios, we solve for the new equilibrium and compare equilibrium outcomes within each counterfactual. The profit changes are measured relative to the case in which the cost of hosting is at 100% of its estimated value.

From the first counterfactual, we plot the percentage change in hotel profits as the cost of Airbnb hosts varies in the first plot in Figure 10. We find that hotel profits increase (decrease) as Airbnb host costs increase (decrease). Interestingly, high-end hotels benefit more from higher Airbnb host costs, while they also suffer more from lower Airbnb host costs. This means that, on the one hand, policies such as charging hotel tax are more favorable to high-end hotels than to low-end hotels; on the other hand, services that facilitate hosting or the trend of "professionalism" are also more harmful to high-end hotels. Another noteworthy finding is that the benefit of higher Airbnb host costs levels off as the costs increase while the loss from lower Airbnb host costs continues to decrease as the costs decrease. Therefore,

[29]The Transient Occupancy Tax rates in San Francisco and Los Angeles are both 14%. For the full list of regions where hotel tax is imposed, see `https://www.airbnb.com/help/article/653/in-what-areas-is-occupancy-tax-collection-and-remittance-by-airbnb-available`.

[30]For instance, see `https://learnairbnb.com/optimize-airbnb-save-time-money/`.

[31]See `https://skift.com/2014/05/30/the-professionalization-of-airbnb-hosts/`.

[32]`https://www.nytimes.com/2017/06/17/technology/airbnbs-hosts-professional-hotels.html`.

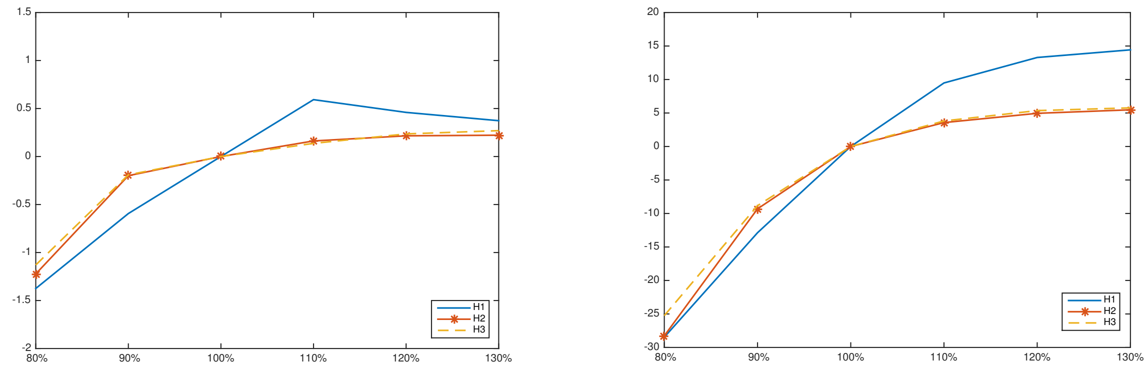
imposing stricter regulations that raise the cost of hosting on Airbnb does not help hotel profitability beyond a certain point, yet reducing Airbnb host costs can increasingly hurt hotel profitability.

Although Airbnb host costs affect hotel profitability, the magnitude of the impact is relatively small. We find that the impact can increase dramatically once we remove business travelers' lower valuation of Airbnb in the second counterfactual. In other words, allowing Airbnb to behave like hotels makes hotels much more vulnerable to changes in Airbnb host costs. As shown in the second plot in Figure 10, hotel profitability can decrease by as much as 25% and increase by as much as 15%. On the one hand, policies that raise Airbnb hosting costs can substantially benefit the hotels once Airbnb provides more hotel-like standardized services. These policies are particularly helpful for high-end hotels, as they face more competition from Airbnb for their core customers (i.e., business travelers). On the other hand, hotels could be much more vulnerable to reductions in Airbnb host costs.

In general, the results suggest that the impact of public policies and Airbnb changes that affect hosting costs crucially depends on whether Airbnb attempts to behave more like hotels and competes head-to-head with hotels. If Airbnb can successfully attract business travelers, hotels could face a real threat from Airbnb in the long run. Note that the counterfactual analysis here is based on optimal pricing in equilibrium. In practice, hotel pricing has not been systematically adjusted after Airbnb's entry because hotels are still using their existing algorithms for revenue management without accounting for Airbnb. As Airbnb continues to grow, the next-generation software may provide such capability. The counterfactual results can be seen as forward-looking and would be relevant once hotel pricing has been systematically adjusted in the future.

Figure 10: Counterfactual: Varying Airbnb Host Costs

(a) Scenario 1 (b) Scenario 2



Notes: The x-axis represents Airbnb host cost as a percentage of the estimated costs. The y-axis represents the percentage change in hotel profits compared to the default case. Scenario 1 varies Airbnb host costs, and Scenario 2 further removes business travelers' lower valuation of Airbnb.

7.4 Robustness of Results: Within-tier Hotel Competition and Capacity Constraint

One caveat of our supply-side problem is that we assume that hotels solve for a tier-level pricing problem without capacity constraints. In this subsection, we discuss the motivation for this assumption and use a simulation to illustrate how relaxing this assumption may impact our main findings. Details of the simulation are in the appendix.

First, we solve for the tier-level pricing problem because we do not have individual hotel-level demand data and cannot set up a demand model and a pricing problem at the hotel level. In practice, there is some evidence that hotels within the same tier cooperate when setting prices to maintain the mark-ups for profitability (e.g., Kalnins 2006). Nevertheless, we conduct a simulation to incorporate within-tier hotel competition. We assume that there are two hotels within the same tier that share the same observed prices (allowed to be different in the counterfactual) and observed characteristics. This setup allows for a stronger within-tier competition than a setup with two hotels of different observed characteristics. It also allows hotels within the same tier to be closer substitutes than hotels across different tiers. We make necessary adjustments to the demand model and the supply-side problem to ensure that doubling the number of hotels does not artificially change the model fundamentals.

Second, we do not include a capacity constraint in the main specification because the simulated demand in equilibrium is smaller than the maximum observed demand, which suggests that the capacity constraint might not be binding. In the data, the maximum observed occupancy rate is approximately 95%. In practice, hotels may be motivated to charge higher prices given lower remaining capacity. To illustrate how a capacity constraint may impact our main findings, we use the maximum observed demand as a proxy for the capacity constraint, which is stricter than using the actual hotel capacity. We impose this capacity constraint in the same simulation as discussed above.

We re-solve for the new equilibrium pricing and compare it with the original optimal pricing. We find that hotels in the new equilibrium charge lower prices overall due to within-tier competition; the new prices are closer to the observed prices. The proposed pricing strategies remain qualitatively the same (i.e., some hotel types in some cities should conduct less seasonal pricing or even counter-seasonal pricing), except that the magnitude of the price changes is smaller. On one hand, the price increase during the low-demand season is smaller due to the within-tier competition. On the other hand, the price decrease during high-demand season is limited by the capacity constraint. We find that the capacity constraint is not binding except for high-end hotels in Miami during high-demand seasons. When trying to conduct counter-seasonal pricing and reduce prices, hotels cannot reduce prices as much as in the unconstrained problem, and therefore, they charge a higher price than in the unconstrained problem. Finally, we also conduct the counterfactual analysis in Section 7.3 using the new setup and find that the results are qualitatively the same as well.

We conclude by summarizing how allowing for within-tier competition and a capacity constraint can impact the optimal pricing strategy. To conduct counter-seasonal pricing, firms raise prices during low-demand season (feature 1) and reduce prices during high-demand season (feature 2). The within-tier competition limits hotels' ability to raise prices in low-demand seasons (feature 1). The capacity constraint limits hotels' ability to lower prices in high-demand seasons (feature 2). Therefore, the proposed pricing strategy in Section 7.2.1 without within-tier competition and a capacity constraint can be regarded as an upper bound in terms of the magnitude of the price change. In our simulation, these two factors do not appear to qualitatively affect the proposed pricing strategy because the underlying incentives to reduce seasonal pricing comes from Airbnb's supply elasticity, which remains unchanged after introducing within-tier competition and a capacity constraint. Hotel competition and capacity constraint are among the main drivers of traditional hotel pricing strategies. The introduction of Airbnb serves as an additional incentive for hotels to consider less seasonal pricing.

8 Conclusion

We study how the entry of flexible-capacity sharing economy platforms affects the competitive landscape in traditional industries with fixed capacity and volatile demand. In the context of Airbnb and hotels, we find that Airbnb mildly cannibalizes hotel sales and expands the market for the industry. The flexible supply from Airbnb helps accommodate demand volatility and amplifies the underlying demand. It also provides incentives for some hotel types in some cities to conduct less seasonal pricing or even counter-seasonal pricing. Market conditions (e.g., seasonality patterns, hotel prices and qualities, consumer composition; the level of Airbnb presence and Airbnb supply elasticity) play a crucial role in determining the impact of Airbnb on hotel sales and hotels' strategic response.

Two modeling decisions are crucial for correctly evaluating Airbnb's impact. First, addressing the endogeneity in seasonal firm conduct is important, as both demand and supply are seasonal in this industry. Second, recovering the underlying demand or consumers' propensity to travel is important, as the observed demand is a result of both the underlying demand and supply-side strategies.

The counterfactual results suggest that Airbnb's recent attempt to behave more like hotels could have a material impact on hotels, especially high-end hotels, by increasing the vulnerability of high-end hotels to lower Airbnb hosting costs. When hosting costs on Airbnb vary, high-end hotels benefit the most from higher Airbnb hosting costs and suffer the most from lower Airbnb hosting costs. High-end hotels should pay close attention to the recent changes in Airbnb's positioning to business travelers and attractiveness to potential hosts.

Our results have managerial and policy implications for other industries where the entry of flexible-capacity sharing platforms has affected the existing business models with capacity or price rigidity. For instance, Uber offers flexible supply and pricing, while taxi companies have relatively fixed capacity and pricing. How the entry of Uber will affect the competitive landscape in the taxi industry is unclear. Studying the impact of the sharing economy in other industries can be a promising avenue for future research. Doing so will also help us to generate potentially similar findings across a number of sharing markets.

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Appendix

A. Robustness Check: Varying Potential Market Size

The total market size is defined as three times the maximum number of monthly travelers by air in the data sample period. Suppose there are four months in total in the sample and the number of air travelers is 100, 110, 120, and 115, respectively. Then, the market size is defined as 120*3=360 for all seasons. The observed number of visitors by air per month is an imperfect proxy for people who actually traveled to the city because a) it does not include people who travel by other transportation means and b) it includes people who travel but do not need accommodations (e.g., they are returning home). In addition, it does not include people who are interested in travel but do not travel because of unattractive options (an important source of market expansion). Therefore, it is not desirable to use the number of visitors by air directly. We instead use three times the maximum monthly number of visitors by air, which is large enough to include people who travel by other means and people who do not travel but who are interested in traveling. Meanwhile, it maintains the difference in market size across cities.

As a robustness check, we vary the multiplier by defining market size as two times or four times the maximum number of visitors by air. As shown in Table 9 and Table 10, most of the parameter estimates are very robust to different multipliers. The only parameters that changed are the fraction of leisure travelers and the price coefficients: as the multiplier increases, the estimated fraction of leisure travelers increases and the price coefficients become more negative. This finding is expected because, as market size increases, the fraction choosing the outside option increases; to rationalize this result, there need to be more leisure travelers who are less likely to travel and who are more price sensitive. Despite the change in parameter estimates, we find that the results for cannibalization, seasonality, and optimal supply-side strategies are very robust to the choice of the multiplier.

Finally, the monthly traveler data we obtain are at the market level. We impute the tract-level number of monthly travelers in the following way. In the data, the observed tract-level demand for tracts within the same city follows almost the same seasonality patterns. The relative magnitudes of tract-level demand also remain the same over the seven years, which may suggest that each tract within the same city accounts for a stable share of the market. To impute tract-level visitors from city-level visitors, we assume that this share of demand is the same as the share of visitors. For each tract, we compute the ratio of observed tract-level demand to city-level demand, average it over time, and multiply it by the city-level market sizes to obtain the tract-level market sizes.

B. Control Function Regression Results

Table 11: Control Function Regression

DV: Hotel price	H1	H2	H3
$p^H_{1m,t-12}$	0.856** (0.0132)	0.0165* (0.0086)	0.0346** (0.0089)
$p^H_{2m,t-12}$	0.0506* (0.0246)	0.854** (0.0160)	0.0740** (0.0166)
$p^H_{3m,t-12}$	-0.0818** (0.0231)	0.0539** (0.0150)	0.703** (0.0156)
Attributes x^H_{jmt}	Yes	Yes	Yes
Seasonality τ^{pH}_{Mt}	Yes	Yes	Yes
R^2	0.926	0.910	0.871
F stat	1942.5	N	4947

DV: Airbnb Price	A1	A2	A3
Attributes x^A_{jmt}	Yes	Yes	Yes
Seasonality τ^{pA}_{Mt}	Yes	Yes	Yes
R^2	0.892	0.913	0.893
F stat	36.2	N	765

DV: Airbnb Supply (in thousands)	A1	A2	A3
Age	0.0075 (0.0049)	-0.0691** (0.0132)	-0.0334** (0.0781)
Income	0.0005 (0.0003)	0.0141** (0.0008)	0.0021** (0.0005)
With Children	0.1194 (0.2487)	-4.735** (0.6639)	-1.532** (0.3932)
Married	-0.3291 (0.2095)	1.283* (0.5593)	0.3136 (0.3313)
Edu: Bachelor	0.5558** (0.0749)	-2.454** (0.2000)	-0.1336 (0.1184)
Work: Unemployment	2.496** (0.415)	0.8908 (1.109)	2.162** (0.6573)
Legal Regulation	Yes	Yes	Yes
Seasonality τ^n_{Mt}	Yes	Yes	Yes
R^2	0.619	0.717	0.606
F stat	104.1	N	765

Notes: * and ** represent significance at the 5% and 1% levels. Legal regulations of Airbnb variables include framework, restrictions, licensing, enforcement.

Table 9: Parameter Estimates: Potential Market Size = 2 * Max Monthly Visitors

		Est	Std			Est	Std
Product FE θ_j	H1	-1.405**	0.0069	Price $\bar{\alpha}_i$	Business	-0.000139**	5.312e-6
	H2	-0.863**	0.0251		Leisure	-0.0114**	2.008e-4
	H3	-1.671**	0.0213	Convention Space $\bar{\beta}_i^{conv}$	Business	1.997**	0.0098
Product FE θ_j	A1	0.654**	0.0581		Leisure	1.264**	0.0133
	A2	-0.302**	0.0190	Std σ^{conv}		0.0666**	0.0032
	A3	-0.909**	0.0437	Ski/Spa/Golf/Boutique $\bar{\beta}_i^{spa}$	Business	0.812**	0.0234
Product FE:	A1	-3.960**	0.0527		Leisure	-1.767**	0.0215
Business θ_{ij}^A	A2	-3.039**	0.0564	Std σ^{spa}		0.0413**	0.0011
# of Hotels γ_{0j}	H1	3.212**	0.0142	Restaurant β^H		-0.0489**	0.0016
(in hundreds)	H2	1.472**	0.0192	All Suites		0.193**	0.0522
	H3	2.229**	0.0179	# of Bedrooms		0.420**	0.0346
# of Airbnb γ_{1j}	A1	6.980**	0.0663	# of Bathrooms		-0.510**	0.0863
(in thousands)	A2	4.817**	0.0811	Overall Rating		-1.886	1.107
	A3	3.662**	0.0718	# of Reviews		0.0266*	0.0163
# of Airbnb:	A1	-2.596**	0.0466	Heating β^A		2.005**	0.0723
Quadratic γ_{2j}	A2	-1.436**	0.0610	Kitchen		2.206**	0.0419
(in thousands)	A3	-1.410**	0.1671	Dryer		0.139*	0.0690
Residual:	H1	3.336**	0.0044	Doorman		-1.909**	0.0965
Hotel Price λ_{1j}	H2	2.293**	0.0215	Intercom		0.322**	0.0802
	H3	4.491**	0.0044		Los Angeles	0.785**	0.0424
Residual:	A1	0.663**	0.0544		San Francisco	0.660**	0.0436
Airbnb Price λ_{2j}	A2	0.877**	0.0381		D.C.	0.710**	0.0083
	A3	0.250**	0.0893	Fraction of Leisure γ_{iM}	Miami	0.784**	0.0411
Residual:	A1	0.140**	0.0656		Chicago	0.830**	0.0882
Airbnb Supply λ_{3j}	A2	-0.0273	0.0862		Austin	0.782**	0.0710
	A3	0.0479*	0.0218		New Orleans	0.890**	0.0124
Time Trend: β_{T1}		0.0517	0.0320		Seattle	0.830**	0.0345
Time Trend: Quadratic β_{T2}		0.0065**	0.0024				
Time Trend: Airbnb β_{TA}		0.129**	0.0371	Nested Logit σ		0.0010**	2.823e-5

Notes: * and ** represent significance at the 5% and 1% levels. "H1, H2, and H3" represent high-end, mid-range, and low-end hotels, respectively. "A1, A2, and A3" represent an entire home/apartment that is not hotel comparable, an entire home/apartment that is hotel comparable, and a private room, respectively.

Table 10: Parameter Estimates: Potential Market Size = 4 * Max Monthly Visitors

		Est	Std			Est	Std
Product FE θ_j	H1	-1.664**	0.0081	Price $\bar{\alpha}_i$	Business	-0.000143**	4.112e-6
	H2	-1.328**	0.0253		Leisure	-0.0155**	3.933e-4
	H3	-2.214**	0.0211	Convention Space $\bar{\beta}_i^{conv}$	Business	1.977**	0.0063
Product FE θ_j	A1	0.702**	0.0584		Leisure	1.257**	0.0109
	A2	-0.317**	0.0185	Std σ^{conv}		0.0666**	0.0035
	A3	-0.958**	0.0488	Ski/Spa/Golf/Boutique $\bar{\beta}_i^{spa}$	Business	0.533**	0.0182
Product FE:	A1	-4.832**	0.0552		Leisure	-1.826**	0.0212
Airbnb θ_{ij}^A	A2	-3.795**	0.0559	Std σ^{spa}		0.0413**	0.0009
# of Hotels γ_{0j}	H1	2.813**	0.0144	Restaurant β^H		-0.392**	0.0020
(in hundreds)	H2	1.330**	0.0190	All Suites		0.0537**	0.0429
	H3	2.032**	0.0173	# of Bedrooms		0.447**	0.0354
# of Airbnb γ_{1j}	A1	6.997**	0.0646	# of Bathrooms		-0.513**	0.0865
(in thousands)	A2	4.799**	0.0809	Overall Rating		-1.958	1.017
	A3	3.644**	0.0702	# of Reviews		0.0346*	0.0162
# of Airbnb:	A1	-2.587**	0.0471	Heating β^A		1.998**	0.0737
Quadratic γ_{2j}	A2	-1.482**	0.0595	Kitchen		2.194**	0.0423
(in thousands)	A3	-1.418**	0.1662	Dryer		0.124	0.0687
Residual:	H1	3.337**	0.0044	Doorman		-1.914**	0.0946
Hotel Price λ_{1j}	H2	2.291**	0.0219	Intercom		0.316**	0.0801
	H3	4.487**	0.0044		Los Angeles	0.858**	0.0425
Residual:	A1	0.666**	0.0547		San Francisco	0.778**	0.0426
Airbnb Price λ_{2j}	A2	0.876**	0.0381		D.C.	0.800**	0.0082
	A3	0.250**	0.0893	Fraction of Leisure γ_{iM}	Miami	0.847**	0.0418
Residual:	A1	0.188**	0.0655		Chicago	0.887**	0.0912
Airbnb Supply λ_{3j}	A2	-0.950	0.0871		Austin	0.839**	0.0755
	A3	0.0405*	0.0198		New Orleans	0.915**	0.0116
Time Trend: β_{T1}		0.0511	0.0282		Seattle	0.869**	0.0356
Time Trend: Quadratic β_{T2}		0.0048*	0.0022				
Time Trend: Airbnb β_{TA}		0.138**	0.0334	Nested Logit σ		0.0010**	2.771e-5

Notes: * and ** represent significance at the 5% and 1% levels. "H1, H2, and H3" represent high-end, mid-range, and low-end hotels, respectively. "A1, A2, and A3" represent an entire home/apartment that is not hotel comparable, an entire home/apartment that is hotel comparable, and a private room, respectively.

C. Robustness Check: No Pre-specified Heterogeneity

As shown in Table 12, the estimates from the model specification without pre-specified heterogeneity (i.e., n_{jmt}^{A} accounts for all rooms for both segments) are very robust compared to those from the main specification in Table 4.

D. Cannibalization Across Cities

In Table 13, we present the market attributes, the estimated fraction of leisure travelers, and the percentage change in total hotel sales for each city. Miami has the most seasonal demand and relatively less expensive high-end hotels, so cannibalization is the second highest there. Austin and Seattle have more seasonal demand and lower quality low-end hotels. The estimated fraction of leisure travelers is among the highest in these two cities. Cannibalization in these cities is also greater. A longer and stronger Airbnb presence can also lead to stronger cannibalization. Los Angeles and San Francisco have lower quality low-end hotels and a longer Airbnb history. The cannibalization in these cities is among the highest.

E. Robustness Check: Alternative Airbnb Pricing Strategy

We estimate how Airbnb prices change with hotel prices in the data using Equation 9 and assume that the estimated coefficients remain the same in the counterfactual. Given that hotel prices differ from the observed prices in the counterfactual, Airbnb pricing rules may also be different from the observed prices in the counterfactual. As a robustness check, we vary the coefficients on hotel prices in Equation 9 and re-solve for the new equilibrium. In Scenario 1, we let the coefficients take the average value of the three tiers, $\widetilde{\kappa}_j^{Al} = \frac{1}{3}\sum_{j=1,2,3}\kappa_j^{Al}$, so Airbnb pricing accounts for the three hotel tiers equally. In Scenario 2, we reduce the largest coefficient among the three hotel types by 0.1 and raise the second largest coefficient by 0.1; thus, Airbnb pricing accounts less for the hotel tier with the largest weight and accounts

Table 12: Parameter Estimates: No Pre-specified Heterogeneity

		Est	Std			Est	Std
Product FE θ_j	H1	-1.571**	0.0078	Price $\bar{\alpha}_i$	$i = 1$	-0.000142**	4.463e-6
	H2	-1.134**	0.0249		$i = 2$	-0.0139**	2.598e-4
	H3	-1.996**	0.0211	Convention Space $\bar{\beta}_i^{conv}$	$i = 1$	1.985**	0.0067
Product FE θ_j	A1	0.674**	0.0573		$i = 2$	1.256**	0.0111
	A2	-0.325**	0.0197	Std σ^{conv}		0.0666**	0.0035
	A3	-0.921**	0.0496	Ski/Spa/Golf/Boutique $\bar{\beta}_i^{spa}$	$i = 1$	0.654**	0.0192
Product FE:	A1	-5.258**	0.0683		$i = 2$	-1.813**	0.0215
Airbnb θ_{ij}^A	A2	-3.766**	0.0718	Std σ^{spa}		0.0413**	0.0011
	A3	-2.694**	0.0622	Restaurant β^H		-0.217**	0.0016
# of Hotels γ_{0j}	H1	2.943**	0.0147	All Suites		0.109**	0.0472
(in hundreds)	H2	1.395**	0.0194	# of Bedrooms		0.405**	0.0362
	H3	2.142**	0.0186	# of Bathrooms		-0.530**	0.0867
# of Airbnb γ_{1j}	A1	6.988**	0.0656	Overall Rating		-1.953	1.219
(in thousands)	A2	4.801**	0.0809	# of Reviews		0.0372*	0.0172
	A3	3.650**	0.0711	Heating β^A		1.997**	0.0731
# of Airbnb:	A1	-2.593**	0.0477	Kitchen		2.191**	0.0427
Quadratic γ_{2j}	A2	-1.470**	0.0599	Dryer		0.126	0.0685
(in thousands)	A3	-1.416**	0.1673	Doorman		-1.914**	0.0958
Residual:	H1	3.336**	0.0044	Intercom		0.316**	0.0806
Hotel Price λ_{1j}	H2	2.291**	0.0216		Los Angeles	0.829**	0.0411
	H3	4.488**	0.0043		San Francisco	0.738**	0.0422
Residual:	A1	0.663**	0.0540		D.C.	0.768**	0.0081
Airbnb Price λ_{2j}	A2	0.875**	0.0381	Fraction of Segment $\gamma_{i=2,M}$	Miami	0.826**	0.0411
	A3	0.250**	0.0893		Chicago	0.866**	0.0894
Residual:	A1	0.167**	0.0644		Austin	0.824**	0.0707
Airbnb Supply λ_{3j}	A2	-0.0552	0.0579		New Orleans	0.911**	0.0118
	A3	0.0349**	0.0124		Seattle	0.8612**	0.0353
Time Trend: β_{T1}		0.0424	0.0298	Nested Logit σ		0.0010**	2.822e-5
Time Trend: Quadratic β_{T2}		0.0068*	0.0032				
Time Trend: Airbnb β_{TA}		0.1290**	0.0381				

Notes: * and ** represent significance at the 5% and 1% levels. "H1, H2, and H3" represent high-end, mid-range, and low-end hotels, respectively. "A1, A2, and A3" represent an entire home/apartment that is not hotel comparable, an entire home/apartment that is hotel comparable, and a private room, respectively.

Table 13: Cannibalization by City

	Market Conditions			Fraction of	Cannibalization:
	Seasonality	Price	Quality	Leisure	% Change in
	($m \equiv \frac{M_1}{M_0}$)	($p \equiv \frac{p^H}{p^L}$)	($l \equiv \frac{v^L}{v^H}$)	(%)	Hotel Sales
Los Angeles	0.24	2.33	0.012	83	-0.62
San Francisco	0.21	2.12	0.014	74	-0.81
D.C.	0.27	2.14	0.017	77	-0.14
Miami	0.29	2.03	0.056	82	-0.66
Chicago	0.23	2.07	0.020	87	-0.06
New Orleans	0.29	2.01	0.001	82	-0.22
Austin	0.27	2.63	0.001	91	-0.49
Seattle	0.25	2.23	0.009	86	-0.41

Notes: The measure of seasonality ($m \equiv \frac{M_1}{M_0}$) is defined as the standard deviation of the season-level demand. To compare across cities, we normalize the demand using the average value for each city. The price premium of high-end hotels ($p \equiv \frac{p^H}{p^L}$) is defined as the ratio of high-end to low-end hotel prices. The relative quality of low-end hotels ($l \equiv \frac{v^L}{v^H}$) is defined as the ratio of low-end to high-end hotel quality (measured as $x^{conv}_{jmt} + x^{spa}_{jmt}$).

more for the hotel tier with the second largest weight. In Scenario 3, we reduce the largest coefficient among the three hotel types by 0.1 and raise the smallest coefficient by 0.1; thus, Airbnb pricing accounts less for the hotel tier with the largest weight and more for the hotel tier with the smallest weight. These changes allow Airbnb to account for the three hotel tiers differently from the observed scenario, while the resulting Airbnb price levels are not artificially raised or reduced.

We find that the results on seasonal pricing are very robust to the changes in coefficients. In general, the coefficients on hotel prices in Equation 9 represent how much Airbnb pricing accounts for the pricing of different hotel tiers. The estimated coefficients are larger if there are more similarities between particular Airbnb and hotel types. Our sense is that as long as these coefficients are positive, the main results will hold because the key feature required to obtain the main results is that higher hotel prices will trigger more Airbnb supply. If the coefficients are positive, higher hotel prices will lead to higher Airbnb prices, which will lead to greater Airbnb supply.

Note that our Airbnb pricing specification may not be as restrictive as it looks; it does not require Airbnb to follow the same seasonal or counter-seasonal pricing pattern as the hotel pricing because Airbnb pricing puts a positive weight on all three hotel tiers. In equilibrium, some hotel tiers may conduct seasonal pricing, while other tiers may conduct counter-seasonal pricing. The overall Airbnb pricing pattern is a weighted result of the three hotel tiers.

F. Robustness Check: Allowing for Within-tier Hotel Competition and a Capacity Constraint

We use a simulation to investigate whether accounting for within-tier hotel competition and a capacity constraint affect our main findings. To introduce within-tier hotel competition, we assume that there are two hotels per tier with the same observed prices (which are allowed to be different in the counterfactual) and hotel characteristics. This setup allows for a stronger within-tier competition than a setup in which two hotels have different observed characteristics. It also allows hotels within the same tier to be closer substitutes than hotels across different tiers. The two hotels are not entirely identical to consumers because they can differ in unobserved characteristics captured by the error terms. To account for the capacity constraint, we impose the constraint that the realized tier-level demand cannot be higher than the maximum observed tier-level demand in a particular city, which we use to proxy for hotel capacity. Given that the two hotels within the same tier are symmetric in the observed characteristics, imposing a tier-level capacity constraint is equivalent to imposing a hotel-level constraint in this context.

Before re-solving for the new equilibrium, we make two necessary adjustments to the demand model and the supply problem to keep the model fundamentals unchanged. On the demand side, consumers now choose among three Airbnb products (indexed by $j = 4, 5, 6$) and six hotel products (two high-end hotels, indexed by $j = 1, 11$, two mid-range hotels indexed by $j = 2, 22$, and two low-end hotels indexed by $j = 3, 33$). We need to ensure that doubling the number of hotel products does not artificially change tier-level hotel market shares and Airbnb market shares. The goal is to let the two hotels within each tier equally split the original market share of that tier, so the tier-level hotel market shares and Airbnb market shares remain unaffected. Denote the original market share of hotel tier j as s_j^0. Denote the new market share of one of the two hotels in the same tier j as s_j. The market shares can be calculated as follows (ignoring the mixed logit form for now for illustrative purposes):

$$s_j^0 = \frac{\exp\left(\theta_j + \alpha p_j + \beta X_j\right)}{1 + \sum_{j=1,2,3} \exp\left(\theta_j + \alpha p_j + \beta X_j\right) + \sum_{j=4,5,6} \exp\left(\theta_j + \alpha p_j + \beta X_j\right)}$$
$$s_j = \frac{\exp\left(\tilde{\theta}_j + \alpha p_j + \beta X_j\right)}{1 + \sum_{j=1,11,2,22,3,33} \exp\left(\tilde{\theta}_j + \alpha p_j + \beta X_j\right) + \sum_{j=4,5,6} \exp\left(\theta_j + \alpha p_j + \beta X_j\right)}$$

Given the same observed p_j and X_j, we keep the estimated preference parameters, except the hotel type fixed effects become $\tilde{\theta}_j = \theta_j + \log \frac{1}{2}$. This transformation ensures that condition $s_j = \frac{1}{2} s_j^0$ holds.

On the supply side, Airbnb prices now change with six hotel prices instead of three hotel prices in equilibrium. We need to make sure that doubling the number of hotel products does not artificially change Airbnb prices, given the same hotel prices. Denote the original Airbnb prices as p_{lmt}^{A0*} and the new Airbnb prices as p_{lmt}^{A*}. We have

$$p_{lmt}^{A0*} = \left(\sum_{j=1,2,3} \kappa_j^{Al} p_{jmt}^{H*} \right) + \hat{\Delta}_{lmt}^{p}$$
$$p_{lmt}^{A*} = \left(\sum_{j=1,11,2,22,3,33} \tilde{\kappa}_j^{Al} p_{jmt}^{H*} \right) + \hat{\Delta}_{lmt}^{p}$$

For the condition $p_{lmt}^{A*} = p_{lmt}^{A0*}$ to hold, we keep the estimated parameters in the equation above except that the coefficients on hotel prices become $\tilde{\kappa}_j^{Al} = \frac{1}{2} \kappa_j^{Al}$. This transformation ensures that, given the same set of hotel prices p_{jmt}^{H*}, Airbnb pricing is not affected by doubling the number of hotel products.

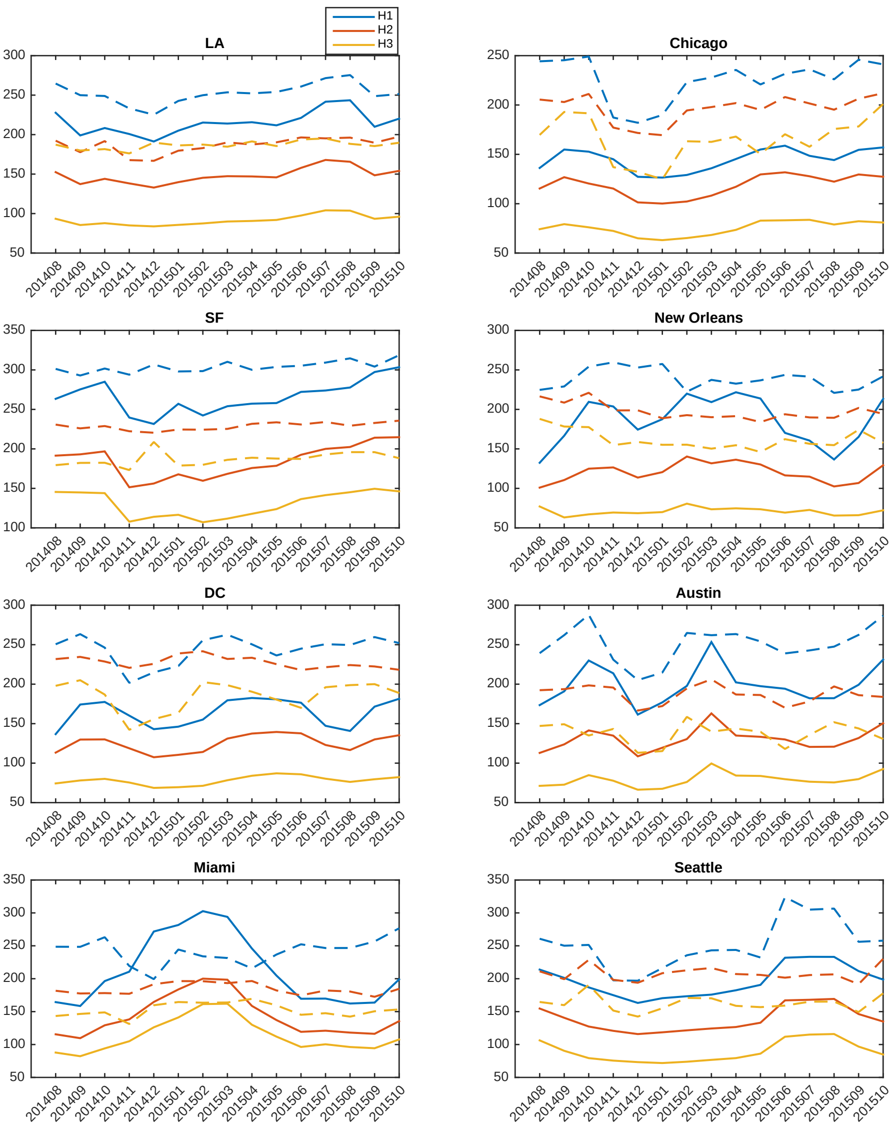
We re-solve for the new equilibrium and plot the new optimal hotel pricing strategy in Figure 11(a). The two hotels within the same tier set the same optimal price so that their plots overlap. We find that allowing for within-tier hotel competition does not appear to qualitatively affect the main findings (i.e., some hotel types in some cities should consider less seasonal or even counter-seasonal pricing); it affects mainly the magnitude of the price change. Compared with the original optimal pricing strategy in Figure 9, hotels now charge lower prices overall due to within-tier competition; the average proposed prices are closer to the observed ones. The proposed seasonal pricing strategy remains directionally the same. The difference is that, for most cities and hotel types that conducted counter-seasonal pricing earlier, the magnitude of price increase during low-demand seasons is now smaller; within-tier competition limits hotels' ability to raise prices during low-demand seasons. The strategy of a few city-hotel types (e.g., high-end hotels in Austin) changed from counter-seasonal pricing to seasonal pricing, but it remained less seasonal than the observed pricing, suggesting that the proposed strategy of conducting less seasonal pricing and even counter-seasonal pricing still holds.

Similarly, we find that imposing the capacity constraint does not appear to affect the main findings and affects mainly the magnitude of the price change. We find that the capacity constraint is not binding in the new equilibrium except for high-end hotels in Miami during high-demand seasons. When conducting counter-seasonal pricing and reducing prices during high-demand seasons, the predicted demand affects the capacity constraint. Hotels cannot reduce prices as much as in the unconstrained problem, and therefore, they charge a higher price than in the unconstrained problem. In general, the capacity constraint limits hotels' ability to lower prices and imposes a lower bound for counter-seasonal pricing during the high-demand season. In the extreme case, if the capacity constraint is seriously binding, we expect that hotels may find it optimal to continue conducting seasonal pricing, but the degree of seasonal pricing should be smaller due to Airbnb's elastic supply. The proposed strategy of conducting less seasonal pricing still holds.

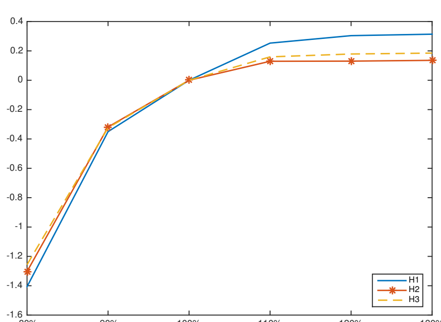
Finally, we conduct the counterfactual analysis in Section 7.3 under the new setup. The results are qualitatively unchanged, as shown in Figure 11(b).

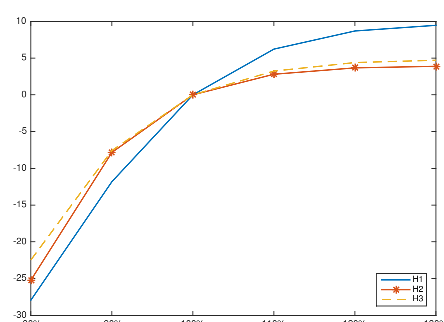
Figure 11: Robustness Check: Allowing for within-tier Hotel Competition and Capacity Constraint

(a) Optimal Hotel Pricing Strategy



(b) Counterfactual Scenarios 1 and 2





X-axis: Airbnb host cost as a percentage of the estimated costs.
Y-axis: % change in hotel profits compared to the default case with the estimated costs.