Pricing Frictions and Platform Remedies: The Case of Airbnb

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Abstract

I document the prevalence of pricing frictions among sellers on Airbnb and quantify the effect of platform policies designed to ameliorate such frictions. Optimal Airbnb prices should reflect varying demand across nights of stay and changes in the opportunity costs over time of booking. However, I demonstrate that, compared to the optimum, sellers' observed prices are much more uniform across nights and rigid over time. I further show that the degree of simplicity is the most prevalent among single-listing sellers, is not captured by several alternative mechanisms, and is most plausibly explained by sellers' cognitive constraints—a limit on the complexity of sellers' pricing strategies. Estimating a structural equilibrium model where sellers set constrained-optimal prices, I find significant frictions amounting to 14% loss in the average consumer surplus and 0-15% profit loss across sellers. Lastly, I demonstrate that an effective remedy is a modified version of the current pricing algorithm that simplifies, but does not completely take away, sellers' pricing decisions.

Keywords: Pricing frictions, Algorithmic pricing, Platform design, Airbnb

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1 Introduction

> "[F]or many hosts, finding the right price for their space can be both time-consuming and challenging... Even many experienced hosts told us that they find pricing difficult, especially as seasons change, special events come to town, and more listings emerge in their neighborhood."
>
> – Janna Bray, Head of Research for Airbnb.[1]

Recent attention has focused on the adoption of advanced pricing technologies by online platforms and their potential effects on market outcomes. A primary motivation for adopting such technologies is to mitigate the substantial pricing frictions sellers encounter. These frictions often result in simplistic pricing policies that do not adequately respond to fluctuating market conditions, a pattern that is more pronounced among amateur sellers, who lack the managerial skills, experiences, or resources to set and maintain optimal prices on their own. Given the prevalence of these frictions, platforms provide various tools and resources to assist sellers in pricing—including pricing algorithms (e.g., Uber and Airbnb), education and training (e.g., Alibaba),[2] and user-friendly interfaces. Which tools should the platform adopt to remedy the pricing frictions?

In this paper, I measure San Francisco Airbnb sellers' pricing frictions, examine their underlying mechanisms, and explore alternative platform designs using counterfactual experiments. I first leverage detailed data to document the extent of pricing frictions among sellers. Then, ruling out alternative explanations, I demonstrate that the primary mechanism is a limit on the complexity of sellers' pricing strategies—a mechanism I refer to as "cognitive constraints." Next, with a structural model where heterogeneous sellers set constrained-optimal prices, I quantify the pricing frictions' impact on consumer, seller, and platform surplus. I find an effective remedy that could alleviate nearly all frictions, which is a platform-provided pricing algorithm that simplifies, but does not completely take away, sellers' pricing decisions.

Airbnb sellers face a difficult pricing problem akin to airline and hotel pricing. Optimal Airbnb prices should be dynamic in nature as they should adjust based on changing opportunity costs (e.g., nights cannot be sold past the check-in date, so they should go on discount as that date approaches). Optimal prices should also vary across nights to reflect the different inherent demand conditions (e.g., nights during a tourist season may sell out quickly, so they should be priced higher). In sharp contrast to the structure of optimal prices, I demonstrate that most sellers adopt simple pricing policies that barely respond to changes in opportunity costs or varying demand

[1] Source: https://airbnb.design/smart-pricing-how-we-used-host-feedback-to-build-personalized-tools/. Accessed in April 2021.

[2] See Alibaba's online seller training videos. https://us.alibaba.com/aste. Extracted in May 2024.

conditions. I also establish that the simplicity of pricing policies is associated with sellers' scale of operation, measured by the number of listings (properties) they operate on the platform. Single-listing sellers display a significant extent of pricing frictions, and in contrast, sellers who manage more listings adopt considerably more sophisticated pricing policies. The extent and heterogeneity of pricing frictions resembles firm heterogeneity in the managers' skills and sophistication, as documented by the previous literature (Goldfarb and Xiao, 2011; Li et al., 2016; Hortaçsu et al., 2019).

I interpret the primary source of pricing frictions as sellers' "cognitive constraint"—a limit in their inherent ability to entertain and adopt sophisticated pricing strategies. I present additional evidence to rule out several canonical economic explanations. One might imagine that adopting a sophisticated pricing policies requires fixed investments that only multi-listing sellers are willing to incur (such as hiring a manager), or information about the market that can be obtained through learning, or efforts to operate the pricing interface to manually set prices. However, leveraging within-seller variation in the number of listings, years of experience, and the introduction of a new feature in the pricing interface, I show that these changes predict no or little price variation. Therefore, I interpret the primary source of pricing frictions as sellers' cognitive constraint, and, by implication, the focus of platform remedies should be to provide direct assistance to seller pricing using an algorithm.

Next, I estimate a structural equilibrium model to quantify the extent of pricing frictions and to explore counterfactual platform designs aiming at mitigating such frictions. The demand side builds on the literature on dynamic pricing of capacity-constrained products (Williams, 2021; Pan and Wang, 2021), where a stream of consumers arrive on the platform, each making mixed logit booking decisions. The supply side extends this literature and characterizes sellers' constrained-optimal pricing decisions. In particular, different types of listings each maximizes its own profits subject to two types of cognitive constraints: a "rigidity" constraint that limits the extent to which prices can vary over time (a Calvo (1983)-type friction), and a "uniformity" constraint that limits the extent to which prices can vary across nights. I flexibly estimate seller heterogeneity in their costs and constraints using an approach similar to Bonhomme et al. (2019).

My estimates reveal that demand is highly seasonal and that consumer composition changes over the lead time (the number of days until the check-in date for that night), implying that optimal prices should indeed vary across nights and over time. These optimal prices sharply contrast with observed prices. Additionally, the estimated price elasticity aligns well with field experimental evidence presented by Jeziorski and Michelidaki (2019).

Supply-side estimates reveal rich heterogeneity in sellers' marginal costs and their cognitive constraints. Only 15% of listings are able to set frictionless prices—that is, prices that vary across nights and can be adjusted at any time. About 35% of listings face some degree of rigidity constraint but no uniformity constraint, implying that they can adjust prices over time, although at a lower frequency compared to optimal dynamic pricing. Further, the remaining half of the listings face total rigidity constraint (cannot adjust prices once set) and, in addition, face different extent of uniformity constraints that often lead to the use of few price points. One prominent example of such behavior is uniform pricing (DellaVigna and Gentzkow, 2019)—one price for all nights that never vary over time—which occurs for about 20% listings. I also estimate the median marginal cost at $38 per night, on par with the city's average hourly wage.

How do these pricing frictions affect equilibrium outcomes? I simulate the counterfactual scenario absent of all pricing frictions. Because prices clear the market for all listings and all nights, virtually all market participants are better off compared to the status quo: consumer surplus would be 14% higher, sellers would gain between 0% and 15% profit, and platform gains 2.5% total revenue.

Given the sizable potential gains, I then ask: what *realistic* remedies can the platform provide to improve market outcomes? Given the nature of pricing frictions, I focus on platform's direct assistance in providing a pricing algorithm and examine two different platform designs around this algorithm. The first design is to completely take over pricing decisions using the platform's revenue-maximizing algorithm, "Smart Pricing" (Ye et al., 2018). This algorithm maximizes expected revenue and does not consider sellers' marginal costs and, anecdotally, often leads to prices that are lower than what sellers are willing to adopt. I find that, if the platform were to enforce this algorithm, prices would have been much lower than the market-clearing level, and sellers would have been worse off—so much so that many would not participate on the platform. I then examine a second design that leverages the algorithm to simplify, but not take away, sellers' pricing decisions. In this design, sellers set one "base price," and the platform makes algorithmic price adjustments around this base price. I find that this "hybrid" algorithm can alleviate virtually all frictions and approach market outcomes in the frictionless scenario. Therefore, ameliorating the pricing frictions is feasible if the platform uses its technology to simplify, instead of taking away, sellers' pricing decisions.

Related literature. The paper's primary contribution is to the recent stream of literature on pricing frictions. Cho and Rust (2010), Pan and Wang (2021), Leisten (2020), Hortaçsu et al. (2021), and Garcia et al. (2022) document the lack of price variation in capacity-constrained industries (rental cars, Airbnb, hotel, and airline) and attribute the frictions to managerial mistakes (Cho and Rust), price-adjustment costs (Pan and Wang), pricing heuristics (Garcia et al.),[3] and organizational frictions (Leisten; Hortaçsu et al.). DellaVigna and Gentzkow (2019), Hitsch et al. (2019),

[3] Garcia et al. (2022) document that managers do react to the price recommendation made by hotels' revenue-management software. However, the reactions are lagged, suggesting that managers still use heuristics (or face menu costs).

Arcidiacono et al. (2020), Strulov-Shlain (2019), and Huang et al. (2020) document grocery prices' (lack of) response to demand features. Bloom and Van Reenen (2010), Bloom et al. (2019), Goldfarb and Xiao (2011), and Hortaçsu et al. (2019) study firm heterogeneity and show that firm size and manager education play a role in firm decision quality.

This paper contributes by presenting evidence that pricing frictions are primarily driven by cognitive constraints—which are limits on the complexity of pricing policies hosts can adopt—and by exploring alternative platform designs as a remedy to sellers' cognitive constraints. The closest related work is Pan and Wang (2021), who present evidence of Airbnb prices' rigidity over the lead time and interpret this rigidity as originating from hosts' price-adjustment costs. Although my modeling approach builds on Pan and Wang (2021), my findings are vastly different: I show that price uniformity across nights is an important ramification of frictions, that the primary source of frictions is *not* sellers' price-adjustment costs, and that a simple revenue-maximizing algorithm does not improve market outcomes due to the inability to account for seller marginal costs.

This paper also extends the previous literature in building a framework to study capacity-constrained markets with pricing frictions. The demand side builds on Williams (2021) and Pan and Wang (2021) but includes a fixed-point algorithm (in line with Goolsbee and Petrin 2004; Chintagunta and Dubé 2005; Tuchman 2019). The supply side extends this literature to characterize sellers' constrained-optimal pricing decisions.

Finally, the paper is broadly related to the recent discussions on algorithmic pricing, with a particular focus on pricing algorithms as a platform design that shapes competing sellers' pricing strategy (in line with Brown and MacKay, 2019). The closest paper is Filippas et al. (2021), who docoument considerable seller exit after a decentralized car-rental platform transitioned from seller pricing to centralized pricing. My paper does not observe such a regime shift, but instead seeks to understand market participants' objectives and constraints and uses this understanding to explore different platform designs. My counterfactual results are in line with Filippas et al.. Also related are Zhang et al. (2021) and Foroughifar and Mehta (2023), who study Airbnb hosts' adoption of Smart Pricing algorithm.[4] Both papers document low adoption rates of the algorithm, an observation consistent with my observation of lack of flexible pricing by hosts. The paper is also broadly related to the vast literature on Airbnb and sharing platforms.[5]

[4]Zhang et al. (2021) document a racial gap in Airbnb sellers' adoption of Smart Pricing. Foroughifar and Mehta (2023) document hosts' low initial adoption of the algorithm and high subsequent termination rates and explain the phenomenon using a learning model.

[5]Pavlov and Berman (2019) present a theoretical model to highlight the tradeoff between platform-centralized pricing (which internalizes the cannibalization effect between sellers) and pricing-in sellers' quality differences. Zervas et al. (2017) estimates the impact of Airbnb listings on hotel revenue and demonstrates a sizable substitution effect, primarily on low-end hotels. Farronato and Fradkin (2018) and Li and Srinivasan (2019) structurally characterize Airbnb and hotels' demand and supply, emphasizing that Airbnb hosts' flexibility plays a crucial role because hotels are capacity constrained. Barron et al. (2020) and Garcia-López et al. (2020) examine the effect of Airbnb listings on rental and housing prices. Fradkin et al. (2018); Zervas et al. (2020); Proserpio et al. (2018); Zhang et al.

2 Background and Data

Background. Airbnb is the leading platform in the short-term rental market. Sellers ("hosts") list their properties ("listings") and set prices. Consumers ("guests") enter city and dates to book accommodations. They pay a nightly price and a per-booking cleaning fee set by the seller, a percentage service fee set by the platform, and taxes set by local authorities. In San Francisco during the sample period, consumers pay a 14% service fee and a 14% lodging tax, and sellers also pay a 3% platform fee.

I do not observe booking rejections by sellers or cancellations by consumers. Most listings either support instant booking or respond quickly to requests,[6] so consumers do not have to wait for sellers' acceptance. Airbnb has a strict cancellation policy during the sample period,[7] and Zeng et al. (2024) estimate the cancellation rate to be low.[8]

Figure 1 displays Airbnb's pricing interface. Sellers can set *one* base price for all nights and *one* distinct weekend price for all Fridays and Saturdays. Additionally, they can manually set nightly prices on the price calendar by first choosing a range of *consecutive* nights, then entering a price, and finally clicking "save" to confirm. Once a night's price is set, it can only be changed by manual adjustments; changing the base price does not impact prices that are already set. Many hosts find it cumbersome to set or change nightly prices.[9]

Airbnb offers "Smart Pricing," a free-to-use pricing algorithm. Opting in the algorithm gives Airbnb full control of pricing (see "Set up Smart pricing" in Figure 1).[10] Ye et al. (2018), from Airbnb, describe that the algorithm estimates a reduced-form consumer demand function using observed prices and solves for the revenue-maximizing prices for each listing.[11] Numerous anec-

(2019) study reputation, reciprocity, and image quality on Airbnb.

[6]Guests can book the preferred listing if the listing supports instant booking (28% listings support instant booking in my sample). If not, guests can inquire about the listing, and 98% of sellers respond to the inquiry within a day (60% of sellers respond to requests within an hour).

[7]During this sample period, Airbnb's cancellation policy is typically much stricter than hotels. 25% of listings employ a "flexible" cancellation policy, allowing cancellation 14 days before check-in (or 48 hours after booking if booked in less than 14 days). The 14% service fee is not refundable (see, e.g., https://www.bnbspecialist.com/airbnb-service-fee-when-refundable/, accessed in September 2021). Beyond the "flexible" cancellation policy, 32% of listings employ a "moderate" policy and 43% employ a "strict" policy, further tightening the window in which a refund (net of service fee) can be issued and increasing the penalty outside of this window.

[8]Zeng et al. (2024) use high-frequency data to measure cancellations from observations where a listing-night first becomes unavailable and later becomes available. Although my data are at a lower frequency, I repeat this exercise and find 3.8% of listing-nights appear to have such a pattern, a number in line with Zeng et al.'s finding, suggesting that cancellations are infrequent.

[9]For example, Joanna14, an experienced Airbnb host, voices her frustration: *"It is proving TOO time consuming to maintain the pricing using the Airbnb standard [interface]... It is just too basic and does not allow enough flexibility!"* Source: https://community.withairbnb.com/t5/Hosting/Lack-of-seasonal-pricing-forcing-me-to-consider-leaving-Airbnb/td-p/328832/. Accessed in April 2021.

[10]There are exceptions: Sellers can override each night's price in the same way as when they manually sets nightly prices. They can also set a price floor and ceiling, which bound the algorithm's price.

[11]Ye et al. (2018) also describes that the algorithm can potentially adjust the price levels based on sellers' desired

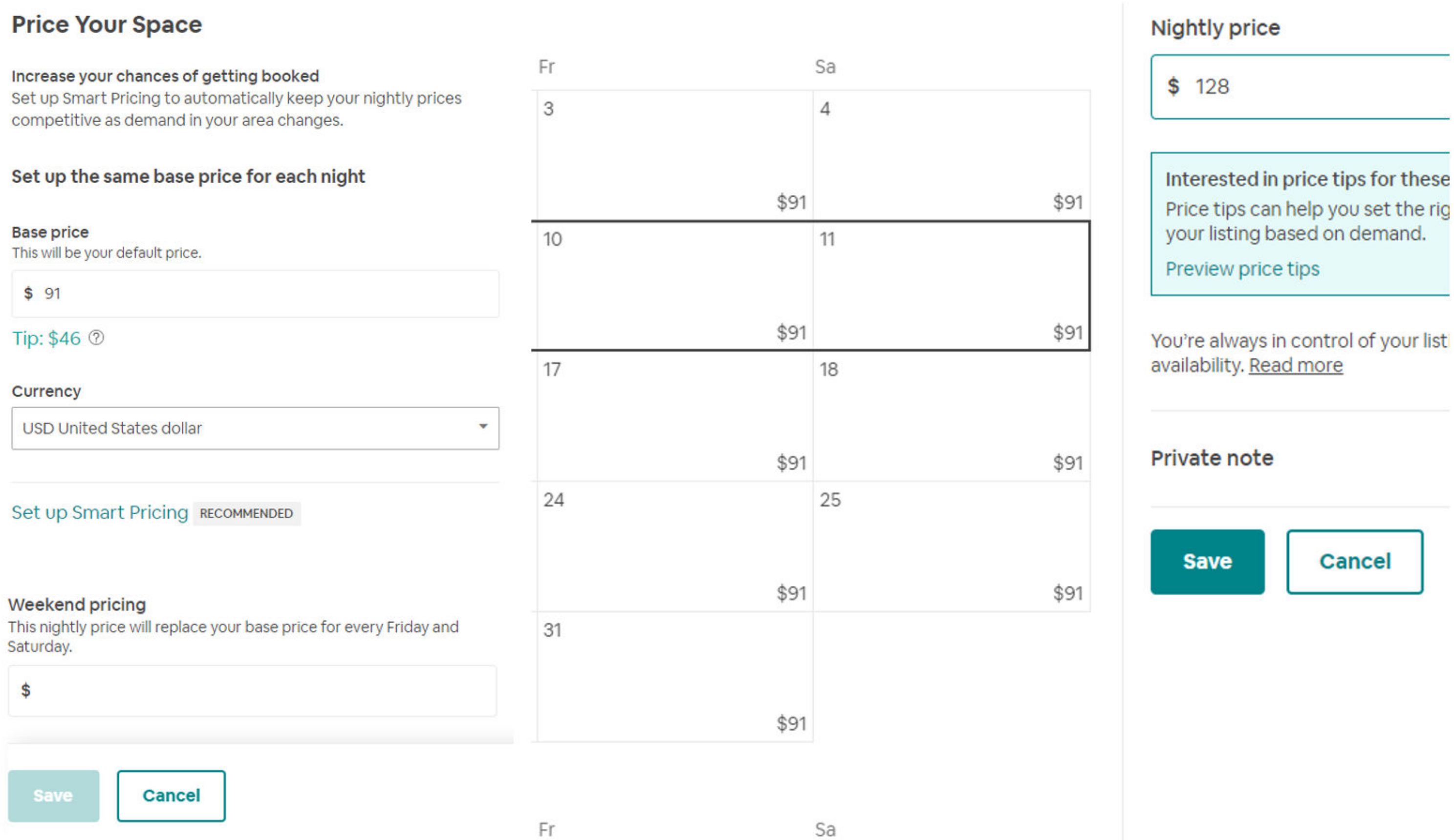


Figure 1: Standard price-setting interface on Airbnb

Notes: This figure presents three aspects of the pricing interface (at different parts of the webpage). The top-left portion is the interface to set one base price for all dates. The bottom-left portion is the interface to set a weekend price (for Friday and Saturday). The right panel is the calendar view, which allows the user to manually set prices for each calendar date (overriding the price set elsewhere) or for a group of consecutive dates that are multi-selected. These screenshots were captured in June 2020.

dotes suggests that sellers wanted higher prices than what the algorithm sets, and consequently, most sellers do not adopt the algorithm.[12,13] In line with anecdotes, Zhang et al. (2021) and Foroughifar and Mehta (2023) show that only about 20-30% of sellers ever adopted Smart Pricing and that most initial adoptors quit using the algorithm within a few months. Further, I conduct interviews with practitioners familiar with the business and confirm that Ye et al.'s version of Smart Pricing is indeed used during the sample period, that the algorithmic prices are indeed close to revenue-maximizing levels, and that the algorithm's adoption rate is indeed low.

Beyond Smart Pricing, Airbnb has made other attempts to help with seller pricing. One particular attempt is a pricing interface change in early 2019, when sellers can set an automated "last-minute discount." Section 3.2 discusses this policy in detail.

Data, sample selection, and interpolation. The data come from Inside Airbnb (`insideairbnb.com`) under the CC0 1.0 Universal License. These data cover all listings from a range of cities and are collected from Airbnb once per month since early 2015. Two datasets are relevant to this research. The first dataset includes listing characteristics on each sampling date t (including the seller's identity, listing features, amenities, location, and average ratings). The second dataset is the calendar data. On sampling date t, I observe whether each *night* τ is available at the time. Booking starts up to one year before check-in, and thus, I typically have 12 monthly observations for each night τ. If a listing-night is available on $t-1$ but unavailable on t, I interpret the night as being booked in this period. If the listing-night is always unavailable for the entire 12-month duration, I interpret the seller as having a "blocked" night τ; that is, it is unavailable from the start.

I take a subsample of Airbnb listings in San Francisco that focuses on (1) the most popular listing types (private rooms and single- and two-bedroom apartments), (2) those who allow a stay duration of three nights or below, and (3) those who offer at least 75% of nights per year. These criteria result in a sample of 18,054 listings, operated by 12,856 sellers, over a period of 54 months, and with 30,864,535 observations at the listing-night-sampling date level (see Appendix A).

The monthly sampling rate creates a truncation problem: if the last sampling date is far from the night of stay, prices might have changed, and the night might be sold, beyond my last observation. To interpolate the occupancy rate, I leverage the fact that some nights are on (or close to) the last sampling date and are not subject to the truncation problem. I interpolate the occupancy rate

levels. However, my interviews with practitioners, who are familiar with this matter, suggests that the algorithmic prices do not deviate much from the revenue-maximizing levels.

[12]See, e.g., https://www.hostyapp.com/smart-pricing-sets-airbnb-rates-low/. Also see numerous forus discussions on reddit/r/airbnb.

[13]Beyond using the platform's algorithm, sellers can use paid third-party pricing software. Typically, using third-party interfaces incurs a fee (usually 1% of total revenue) and requires the sellers to set up the software through Airbnb's API. Although I do not have direct measures of who uses a pricing software, I later demonstrate that price variations are low and display clear patterns consistent with the standard price-setting interface, suggesting the majority of sellers still use the standard interface to set prices.

by matching each night with a similar night close to the sampling date. To interpolate prices, I leverage the observation that pricing strategies are highly simplistic for most listings (section 3), allowing me to fit a simple pricing-policy function for most listings (see Appendix A).

3 Pricing Strategies and Frictions: Empirical Observations

This section presents key empirical findings on pricing frictions and their heterogeneity across sellers. I demonstrate that most sellers set simple prices that do not respond to demand- and opportunity-cost differences, whereas a small fraction of them set sophisticated prices that resemble the pricing algorithm. Then, I demonstrate that these frictions are not primarily explained by sellers' fixed costs (setting up a pricing system), information costs (learning about demand), or price-adjustment costs (effort to operate the pricing interface). Instead, I interpret that these frictions likely arise from an inherent limit on the complexity of some sellers' pricing strategies, referred to as their "cognitive constraints."

3.1 Heterogeneity in pricing strategies

Examples and possible algorithmic pricing. I randomly draw 25 listing-sampling date-level observations and visualize their prices across nights. Figure 2 (A) shows prices follow strong uniformity patterns for most of these listings. Eight listings have completely uniform prices, six listings have weekday-weekend patterns, and most others have large clusters of nights set at the same price. However, a few listings have significantly higher degrees of price variation.

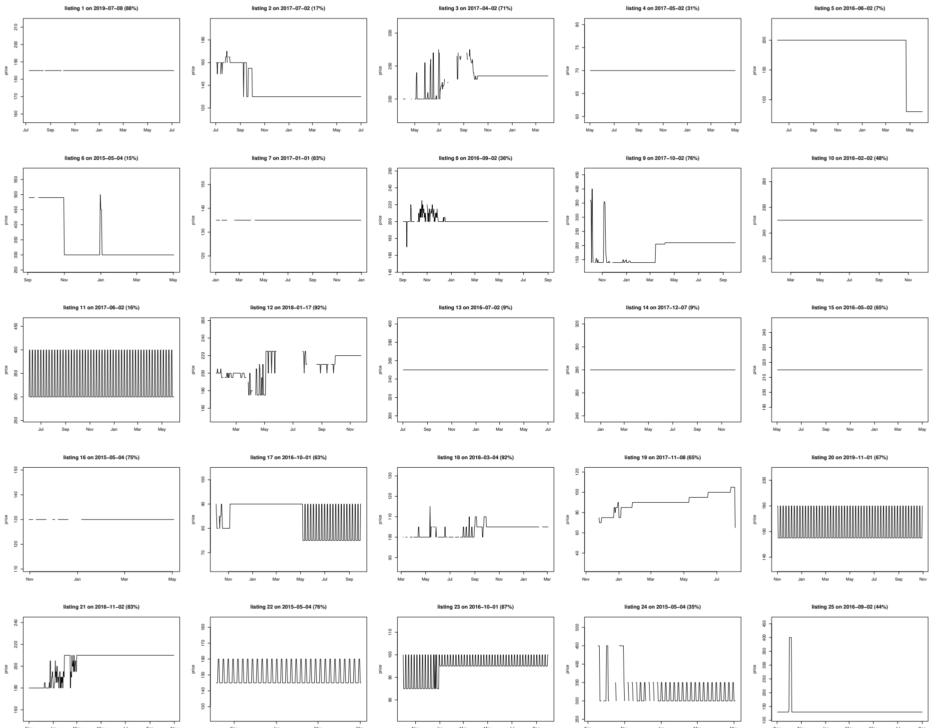
To contrast these prices, I draw another sample from the subset of listings whose degree of price variation (detailed later) resides in the top 5%. As shown in Figure 2 (B), these listings have complex pricing patterns that are difficult to set using the standard interface. Yet, prices do share common, intuitive patterns: they are highly seasonal, feature a polynomial-like baseline price, and exhibit clear weekend patterns. One might speculate that these prices are set by pricing algorithms.

Measures of price variability. To formally study pricing patterns, I construct three measures of price variability. The first measure is the standard deviation of log prices across all nights τ, holding fixed listing j and sampling date t:

$$\text{std}\left(\log\left(\text{price}_{j\tau t}\right)\right)|_{j,t}. \tag{1}$$

This measure represents overall price variability. A lower standard deviation represents simpler pricing policies, and a zero standard deviation corresponds to uniform prices.

(A) All listings



(B) Listings with residual price variation *above* the 95th percentile

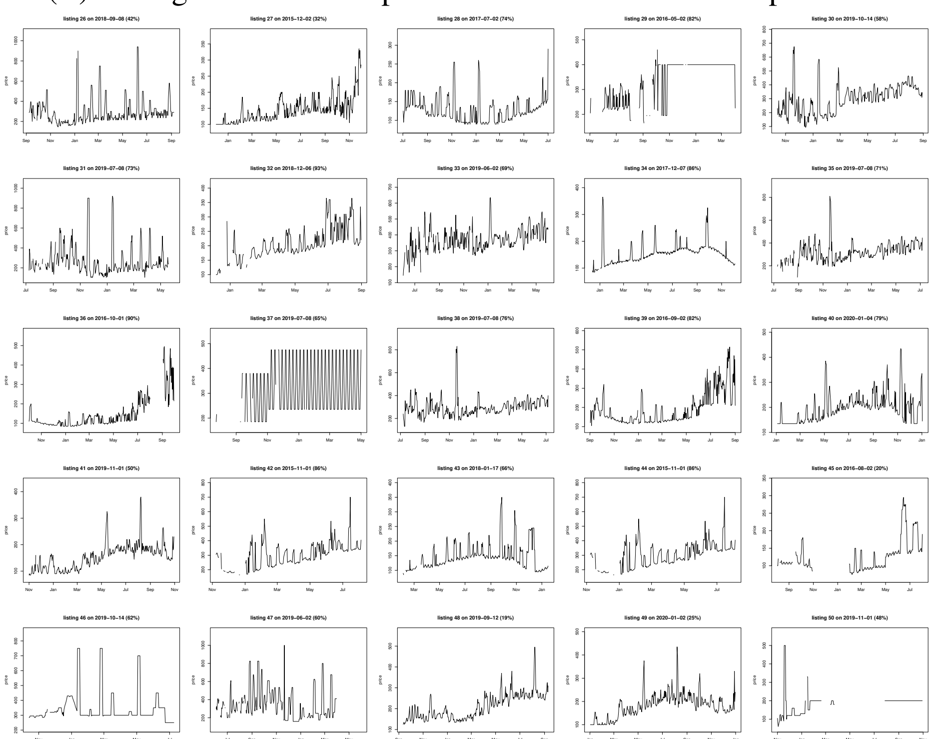


Figure 2: Pricing patterns of randomly drawn listings

Notes: Prices for 50 randomly drawn listings observed on specific dates. The X-axis is the night of the stay. The top 25 are drawn from all listings. The bottom 25 are drawn conditional on the residual price variation above the 95th percentile. All prices are the 365 nights on and after the observation date in the graph title.

The second measure examines the degree of price changes over the lead time—the time until check-in. Optimal Airbnb pricing should adjust dynamically, reflecting the shifting opportunity cost associated with the lead time. A long lead time indicates the night has ample opportunity to be booked, allowing the seller to set a high price in anticipation of a buyer with high willingness to pay. As the lead time diminishes, such opportunity dwindles, and the price should decrease (holding fixed demand and competition). One measure of dynamic pricing is the average percent difference between the price in the final month and the initial price, or

$$\mathbb{E}\left[1-\frac{\text{price}_{j,\tau,12}}{\text{price}_{j,\tau,1}}|j,t\right]. \tag{2}$$

The third measure assesses the degree of price uniformity across demand shifters. It involves calculating the percent price premium for summer (July to September), weekend, and holidays, which represent the extent to which prices capture the underlying demand across nights. I focus on the summer price premium here and present other measures in the appendix.

Summary statistics. In Table 1, I summarize sellers' scale of operation (number of listings) and years of experience in the market, price and occupancy, and different measures of price variability. I find sizable heterogeneity in scale and experience: The median property is operated by single-listing sellers with three years of experience, and a quarter of properties are operated by sellers with at least three listings or at least five years of experience.

I also find considerable heterogeneity across the average occupancy rate and price levels of sellers. The top quartile of sellers are able to fill their properties at least 87% of the time, whereas the properties of the bottom quartile are mostly empty. Prices are considerably dispersed: The 75th quantile of price, at $235, is more than two times that of the 25th quantile at $108.

Further, I find a lack of price variation across nights and over the lead time. The median standard deviation of price across nights is only about 5% of price, or about $7 at the median price. Consistent with the low price variation, the median listing has only four distinct price points per 365 nights. In addition, summer prices are less than 0.4% higher for the median listing, and the last-month (before check-in) prices are 2% lower than the initial price. However, a small fraction of listings do have significant price variations. For example, a quarter of listings show at least an 11% standard deviation in prices, set at least 16 distinct price points, charge at least a 3.5% summer price premium, and provide 10% or more last-month discounts.

The lack of price variation over the lead time, for the majority of listings, are consistent with the degree of price rigidity documented by Pan and Wang (2021). In addition, the lack of price flexibility across nights further suggests Airbnb hosts' inability to set prices that reflect demand differences across nights, in line with Li et al. (2016).

Table 1: Summary statistics across listings

	mean	5 pct	25 pct	median	75 pct	95 pct
total number of listings	4.002	1	1	1	3	11
years of experience on Airbnb	3.622	0	2	3.5	5	7
number of nights supplied (per 365 nights)	329	212	303	360	365	365
occupancy rate	0.612	0.045	0.370	0.693	0.872	0.997
price	188	72	108	150	235	410
std. of log price across nights	0.076	0.000	0.000	0.050	0.110	0.263
number of distinct prices (per 365 nights)	16	1	2	4	16	75
(negative of) %last-month discount	0.05	-0.11	-0.01	0.02	0.10	0.31
%summer price premium	0.024	-0.040	-0.003	0.004	0.035	0.158

Notes: All variables are measured at the listing-month level, and then averaged across months for each listing.

3.2 Main explanation: Persistent seller heterogeneity in cognitive constraints

My primary explanation of the extent of heterogeneity in pricing frictions is that sellers face heterogeneous cognitive constraints. Some sellers can better process the sophisticated market conditions and can adopt a sophisticated pricing policy. Other sellers, who are bound by a tight congnitive constraint, instead adopt simple pricing heuristics. One prominent example of such heuristics is uniform pricing, where the seller charges one price for all nights regardless of the time of the year or the lead time.

Surveys to professional managers (e.g., Hall and Hitch, 1939; Noble and Gruca, 1999) document that they use simple heuristics such as “cost-plus” pricing. More recently, Hortaçsu et al. (2019) show empirically that firm size is a strong predictor of the extent to which their bidding decisions depart from canonical auction models. In my context, most Airbnb sellers are not professional managers, operate only few listings, and lack strategic pricing knowledge or managerial trainings. On the other hand, some sellers operate many listings and, have organized operation routines, and might even make data-driven decisions. The hypothesis is that degree of simplicity in a listing’s pricing strategy depends on the seller’s scale of operations—their number of listings.

To examine whether sellers’ number of listings explain their degree of price variation. I regress listing j’s price variability on seller h’s number of listings,

$$\operatorname{std}\left(\log\left(\text{price}\right)\right)_{jt} = \beta_{\#\text{listing}_{ht}} \mathbb{I}_{\#\text{listing}_{ht}} + \delta_{m(j)t} + X_{jt}\gamma + \varepsilon_{jt}, \tag{3}$$

controlling for neighborhood-sampling time fixed effects ($\delta_{m(j)t}$) and observed characteristics (X_{jt}) to compare among observably similar listings across sellers. X_{jt} includes amenity fixed effects and fully saturated neighborhood$\times$listing type$\times$number of rooms$\times$max number of guests fixed effects.

Figure 3 visualizes the focal parameters of interest, relegating details to Appendix Table B.1 (A). I find that multi-listing sellers often adopt more sophisticated pricing strategies compared to

Figure 3: Across-seller differences in the degree of price variability

Notes: The bar plots present coefficient estimates of equation (3), with the dependent variable being the standard deviation of log price, the percentage past-month discount, and the percentage summer price premium. Whiskers are 95% confidence intervals. For the full table, see Appendix Table B.1 (A).

single-listing sellers. For example, sellers who manage six or more listings display a significant price variation within each listing, where one standard deviation in the prices across nights is 13.1% of that listing's price level. This degree of variation is twice as large as that of single-listing sellers. I observe comparable results when measuring price variability over time, such as the percentage discount from the previous month, and across different nights of stay, such as the percentage premium for summer prices.[14]

One might wonder whether multi-listing sellers face systematically different demand primitives than single-listing sellers. For example, if multi-listing sellers cater more to seasonal travelers, they would set seasonal prices to capture this demand variability. In Appendix B.2, I demonstrate that multi-listing sellers do not face different summer demand shocks, weekend demand shocks, or holiday demand shocks, compared to single-listing sellers. Therefore, the price variability differences cannot be explained by demand-side factors. One might also wonder whether alternative explanations, other than sellers' cognitive constraints, can explain the systematic lack of price variability especially for single-listing sellers. I address several alternative explanations in the subsequent section.

3.3 Alternative explanations

In this section, I discuss and rule out three canonical alternative explanations. In particular, I show that the pricing frictions are not primarily explained by sellers' fixed costs of adopting good

[14]This result extends Li et al. (2016), who show multi-listing hosts charge more distinct prices conditional on a few listing characteristics (Table 8). Appendix B.2 further demonstrates multi-listing sellers' prices are more responsive to demand shocks, in line with Li et al. (2016)'s Table 9 and Leisten (2020).

pricing-decision routines, or their information costs to learn about the market environment, or menu costs to manually adjust prices using Airbnb's pricing interface.

Not explained by fixed costs. One might imagine that sellers need to invest fixed costs to set up a sophisticated decision-making routine, which involves hiring a manager, renting a software system, or monitoring the market conditions. Those with a small scale of operation might not find it optimal to incur these costs, and instead, would rather use simple pricing heuristics. To investigate the fixed costs hypothesis, I estimate the following equation:

$$\text{std}\left(\log\left(\text{price}\right)\right)_{jt} = \beta_{\text{\#listing}_{ht}} \mathbb{I}_{\text{\#listing}_{ht}} + \delta_{m(j)t} + X_{jt}\gamma + \alpha_h + \varepsilon_{jt} \tag{4}$$

where, importantly, I control for seller fixed effect α_h and exploit within-seller variation in the number of listings.

If the primary source of pricing frictions is due to fixed costs, sellers who expand to have additional listings should be more willing to incur these costs. As such, as they expand in scale, they should adopt sophisticated pricing strategies to all listings. However, I find in Figure 4 (A) that the price variability, across all measures, shows little responses to changes in the number of listings *within* a seller. (Y axis scale is the same between Figures 3 and 4.) This finding suggests that pricing frictions are not explained by fixed costs to set up a sophisticated decision-making routine.

Not explained by information costs. One might also imagine that it is costly to obtain information about demand or competitor behavior, and sellers might gradually acquire this information through learning. For example, a seller might learn over time that weekend demand is higher than weekdays, summer demand is higher than winter, or one has to lower the prices on unsold nights when the check-in date is approaching. To examine this hypothesis, I estimate the following equation:

$$\text{std}\left(\log\left(\text{price}\right)\right)_{jt} = \beta_{\text{tenure}_{ht}} \mathbb{I}_{\text{tenure}_{ht}} + \delta_{m(j)t} + X_{jt}\gamma + \alpha_h + \varepsilon_{jt} \tag{5}$$

which is similar to equation (4) except that the focal variables of interest become seller tenure fixed effects (the number of years since the seller first listed on Airbnb).

If the primary source of pricing frictions is due to information costs—at least for the information that can be acquired through learning—one should expect that within seller, the degree of sophistication in their pricing policy functions increases with tenure. However, I show in Figure (4) (B) that sellers, after gaining years of experiences, do not set more sophisticated pricing policy functions. The overall price variability slightly decrease over years of tenure but the change

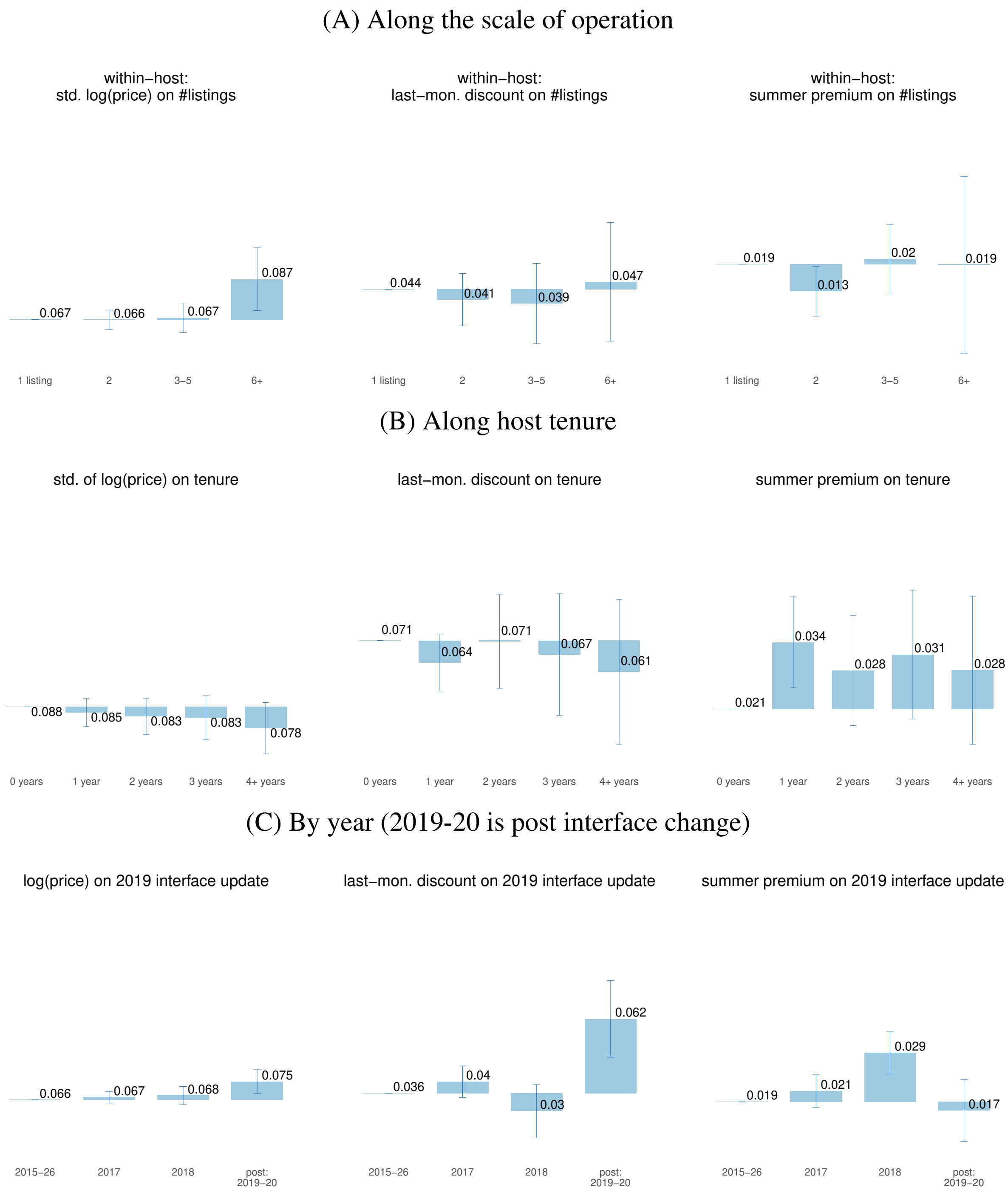


Figure 4: Within-seller changes in price variability along scale, experience, and time

Notes: The bar plots present coefficient estimates of equation (4), with the dependent variable being the standard deviation of log price, the percentage past-month discount, and the percentage summer price premium. In panel (A), the independent variables are number of listing bin fixed effects. In panel (B) they are years of tenure fixed effects. And in panel (C) they are year fixed effects, where the last bin (2019-20) is after the platform introduced the last-minute discount to the pricing interface. Whiskers are 95% confidence intervals. The scale of Y-axis follows Figure (3) for each dependent variable (although the support might differ). For the full table, see Appendix Tables B.1 (B) and B.2 (A) and (B).

is statistically insignificant. The extent of last-month discount barely changes with tenure. And, whereas I do observe a slightly larger summer price premium in year 2, the increase is small and does not persist as the seller gains more experience. Therefore, I conclude that the pricing frictions do not seem to originate from sellers' initial lack of information about the market environment.

Not primarily explained by menu costs of manual price adjustments. A final alternative explanation is that the pricing interface does not make it easy to implement a sophisticated pricing strategy, creating costs to set different prices across nights or to adjust them over time. Pan and Wang (2021) document a lack of price variation over the lead time, interpret the source of this price ridigity as sellers' price adjustment costs, but do not exploit variation in the pricing interface to further test their interpretation. To further test the price adjustment cost hypothesis, I exploit a pricing interface change in early 2019, when Airbnb added "last-minute discounts" to make price adjustments easier for sellers.[15] This feature allows the seller to set a percentage decrease from the regular price if the lead time falls below a threshold (set by the seller), thus reducing the menu costs to adjust prices once for each night of stay.

To investigate this explanation, I estimate

$$\%\text{last-month discount} = \beta_{\text{year}_t} \mathbb{I}_{\text{year}_t} + \tilde{X}_{jt}\gamma + \alpha_h + \varepsilon_{jt} \tag{6}$$

where the main parameters of interest are year fixed effects β_{year_t}, and I also control for observable characteristics $\tilde{X}_{jt}$ and host fixed effects α_h. I also examine other measures of price variability. Only for this analysis, I assume that all differences over time are due to the change in the pricing interface, thus effectively do not control for other time fixed effects or interactions as I do in other specifications. While this might be a strong assumption, I perform placebo tests that β_{year_t} should not be different across other years before 2019.

If the cost of operating the pricing interface is the primary explanation, one should observe more dynamic pricing practices after 2019, when the platform made dynamic pricing automatable using the standard price-setting interface. Figure (4) (C) shows that the pricing interface change does have a positive effect on the extent of dynamic pricing. However, the effect is modest at best. The degree of last-month discount goes up from about 3%–4% before 2019 to about 6% after 2019, an increase of two or three percentage points (pp.). This increase in last-month discount is smaller in magnitude compared to the across-seller differences in Figure 3, which amounts to a four pp. difference between single- and multi-listing sellers. The amount of last-month discount

[15] I use google archives to pinpoint the change date as around January 2019, indicated by a surge of discussion about this feature. A few reports suggest, however, that some hosts received pilot trials of this system in 2018. Although the official website states that this feature is available for hosts with at least two listings, single-listing hosts also report having access to this feature.

is also much smaller than the optimal amount implied by my structural estimates, which is 30% from Table 3. In addition, I discuss in Appendix Section B.3 that many sellers still do not adopt dynamic pricing at all after the interface change, including many multi-listing sellers who should have received notifications about this change. Therefore, although the pricing interface change does increase the extent of dynamic pricing (and I control for this change in the structural model), sellers' cost of operating the pricing interface does not seem to be the primary explanation of the pricing frictions.

4 Structural model and estimation

How can the platform provide remedies to sellers' pricing frictions? In order to quantify the impact of potential remedies, I present and estimate a model of equilibrium demand and supply model, where consumers choose among Airbnb listings, and sellers decide whether to supply their properties on the platform and, if so, set constrained optimal prices. The model uncovers demand primitives and sellers' distribution of marginal costs, pricing frictions, and fixed costs, which are primitives crucial for simulating counterfactual market outcomes. Due to computer memory constraints, the structural model further focuses on studios and single-bedroom apartments (excluding two-bedroom apartments) and uses a random 75% subsample. Appendix C discusses model implementation details.

4.1 Consumer demand for Airbnb

Setup. Two types of consumers ($k = 1,2$) arrive in San Francisco. Consumer i of type k comes in month t and looks for a listing for night τ in zip code m. Her utility from booking listing j is

$$u_{ij}^{k} = \delta_{jq(\tau(i))} + \alpha^{k} \log\left((1+r) \cdot p_{j\tau(i)t(i)}\right) + \xi_{j\tau(i)t(i)} + \varepsilon_{ij}. \quad (7)$$

The consumer does not choose the stay night (τ), market (m), and booking time (t). As such, all three subscripts are fixed given the consumer identity i (subsequently, notations such as $\tau(i)$ are simplified as τ). $\delta_{jq(\tau)}$ are fixed effects for listing j in the quarter of the night, $q(\tau)$, which absorbs amenities, reviews, cleaning fee, and other features that vary infrequently. $p_{j\tau t}$ is the price for night τ if booked in period t. Constant r represents the percent service fees Airbnb charges on top of the list price. $\xi_{j\tau t}$ captures unobserved demand shocks for night τ at time t, which represents, for example, a game taking place on day τ. Because I use a control function to address price endogeneity, I parameterize $\xi_{j\tau t} = \sigma_1 \eta_{j\tau t} + \sigma_2 \eta_{j\tau t}^{2}$, where $\eta_{j\tau t}$ is the error term of a first-stage price equation, and σ_1 and σ_2 are additional scale parameters. ε_{ij} is a Type-1 extreme-value error term.

I normalize $u_{i0} = \varepsilon_{i0}$ if the consumer does not book any listing and takes the outside option.[16] With this structure, we have a logit demand at the consumer-type level:

$$s^k_{j\tau t} = \frac{\exp\left(\delta_{jq} + \alpha^k \log\left((1+r) \cdot p_{j\tau t}\right) + \xi_{j\tau t}\right)}{1 + \sum_{j' \in J_{m\tau t}} \exp\left(\delta_{j'q} + \alpha^k \log\left((1+r) \cdot p_{j'\tau t}\right) + \xi_{j'\tau t}\right)}, \tag{8}$$

where $J_{m\tau t}$ is the available set of listings at time t for night τ in zip code m.

Type k consumers arrive at the Poisson rate of $\lambda^k_{m\tau t}$. I assume the arrival rate depends on the lead time, whether τ is on a weekend or a national holiday, day of the week dw, and month of the quarter mo (the first month of each quarter is normalized to zero, given δ_{jq}'s). Specifically,

$$\lambda^k_{m\tau t} = \gamma^k_{0m} \exp\left(-\gamma^k_1 \cdot (\tau - t) + \gamma^k_2 \cdot \mathbb{I}_{\text{holiday}(\tau)} + \sum_{dw=1,\ldots,6} \gamma^k_{2+dw} \cdot \mathbb{I}_{\text{DOW}(\tau)=dw} + \sum_{mo \in \{2,3,5,6,8,9,11,12\}} \gamma^k_{8+mo} \cdot \mathbb{I}_{\text{MOY}(\tau)=mo}\right). \tag{9}$$

Appendix C.2 presents more details on normalization and identification.

Nested fixed-point algorithm and estimation. My sample contains 33,354 listing-quarter-level intercepts, δ_{jq}'s, which are nonlinear parameters in the model. Jointly estimating them using maximum likelihood is infeasible, yet omitting them (assuming listings only differ in observed characteristics) makes demand too restrictive.[17]

To allow for δ_{jq}'s in the model, I adapt the nested fixed-point algorithm in Goolsbee and Petrin (2004); Chintagunta and Dubé (2005); Tuchman (2019) and use it to estimate capacity-constrained demand models (Williams, 2021; Pan and Wang, 2021; Joo et al., 2020; Hortaçsu et al., 2021). The main idea is to collapse the observed binary occupancy *outcomes* on the listing-night level to compute the continuous occupancy *rates* on the listing-quarter level, and invert the occupancy rates to back out the fixed effects δ_{jq}. Built on Williams (2021) and Pan and Wang (2021), Appendix C.2 derives a closed-form expression for the *quarterly* occupancy rate,

$$\frac{1}{|q|} \sum_{\tau \in q} \text{occupancy}_{j\tau} = \bar{s}_{jq}\left(\delta_q\right) := \frac{1}{|q|} \sum_{\tau \in q} \left(\sum_t \left(1 - \exp\left(-s^1_{j\tau t} \cdot \lambda^1_{m\tau t} - s^2_{j\tau t} \cdot \lambda^2_{m\tau t}\right)\right) A_{j\tau t} \right). \tag{10}$$

[16] Standard with the hotel and airline literature, this assumption imposes that consumers are not forward-looking and do not wait for prices to change. Empirically, consumers have limited incentives to wait, because prices do not decrease much, and good listings are usually off the market quickly. In addition, conversations with practitioners suggest consumers are unlikely to wait for a single listing's price drop (even if they wait for the platform's overall price level to change). As such, it is reasonable for an *individual* listing's pricing to assume static demand. However, this assumption does preclude the platform from considering demand's reaction to a platform-wide dynamic-pricing policy. Allowing for dynamic demand is infeasible within this literature's current framework but is an important future direction for this literature.

[17] For example, a vast literature highlights the importance of reputation (e.g., Fradkin et al., 2018). The reputation effect is consistent with my descriptive evidence that prices tend to increase as the host stays longer on the platform. Also, Zhang et al. (2019) show image quality plays a role in driving demand for Airbnb listings. Reputation (reviews) and pictures are two examples of many unobserved demand shifters.

Denote $A_{j\tau t}$ as the availability of listing j on night τ at the beginning of month t. The left-hand side is the *observed* quarterly occupancy rate. The right-hand side is a closed-form expression of the occupancy rate, which is a function of all listing fixed effects in the quarter, $\delta_q = \left(\delta_{1q}, ..., \delta_{Jq}\right)'$, demand shocks, and other demand parameters.[18] Therefore, given each set of nonlinear parameters $\left(\alpha^1, \alpha^2, \gamma^1, \gamma^2, \sigma\right)$, I solve for δ_{jq}'s by the system of nonlinear equations (10), and then use the solved $\hat{\delta}_{jq}$'s to compute the likelihood function. I then find the nonlinear parameters that maximizes the log likelihood.

Uniform-pricing instrument (control function). Price $p_{j\tau t}$ might be endogeneous to unobserved demand shifters $\xi_{j\tau t}$. These demand shifters potentially capture unobserved local events on night τ or other changes within a listing-quarter. To identify the price coefficient, I leverage the extent of pricing frictions in this market. The main idea is that prices are often set uniformly and adjusted in "batches." In particular, far-apart nights, say, τ', might change prices in the same way as focal night τ *only because* it is convenient for the seller to set one price and adjust this price at the same time. In other words, pricing frictions create supply-side co-movements in prices for otherwise unrelated nights.

Based on this idea, for each focal night τ, I construct the average price for nights τ' in *different quarters* of τ. For each τ', I further use the price in the previous sampling month (i.e., $p_{j\tau',t-1}$) to guard against simultaneity. I show in Appendix D that this "uniform pricing" instrument strongly predicts prices, with an excluded-variable F-statistic on the order of 10,000 in linear specifications with the same set of controls as the structural model. I also show this instrument produces very different results from using the lagged price as an instrument, with the latter potentially endogenous to time-invariant unobservables on each night (e.g., events on given dates). This instruments are, to my knowledge, new to the literature on demand estimation and might have broader applicability beyond Airbnb, given the prevalence of uniform prices driven by supply-side frictions (DellaVigna and Gentzkow, 2019; Adams and Williams, 2019; Hitsch et al., 2019).

Given the nonlinear demand model, I adopt a control function approach similar to Petrin and Train (2010) in which I allow prices to be a function of observables $x_{j\tau t}$ and the uniform pricing instruments (or strictly speaking, excluded variables) $z_{j\tau t}$, or

$$p_{j\tau t} = \left(x_{j\tau t}, z_{j\tau t}\right) \cdot \phi + \eta_{jt\tau}. \tag{11}$$

I estimate this first stage, obtain the residual $\hat{\eta}_{j\tau t}$, and proxy demand shocks using a quadratic

[18] Availability $A_{j\tau t}$ is known in the data during estimation. The fixed point (10) can be solved quickly because $A_{j\tau t}$ is known (different from Tuchman, 2019, who needs to simulate individual states). In the counterfactual, while I need to forward-simulate availability $A_{j\tau t}$, the δ_{jq}'s have been solved (and demand parameters have been estimated), and one does not need to repeat the fixed-point algorithm.

specification of this residual ($\hat{\hat{\xi}}_{j\tau t} = \sigma_1 \hat{\eta}_{j\tau t} + \sigma_2 \hat{\eta}^2_{j\tau t}$). This approach implicitly assumes prices fully capture unobserved demand factors $\xi_{j\tau t}$.

4.2 Pricing decisions

I characterize each listing's pricing decision as a constrained optimization problem, where the listing maximizes expected profits within the bounds of "cognitive constraints." These constraints may limits the listing's ability to adjust prices flexibly over the lead time and to set flexible prices across different nights. For the sake of model tractability, I assume that adjusting prices dynamically (e.g., responding to changes in market structure or opportunity costs) is a more sophisticated task than setting prices to reflect stable demand factors (e.g., charging a summer price premium). This assumption enables me to categorize a listing's pricing decision into two distinct types. The first type sets prices independently for each night, but may face "rigidity constraints" – i.e., have limited opportunities to adjust prices over time. The second type is unable to adjust prices for each night and may also face "uniformity constraints" – i.e., have limited flexibly how prices can vary across different nights.

First, establish notations for each listing's residual demand and profits. Denote the probability that *at least one* consumer books listing j for night τ during month t as $q_{j\tau t}$. Denote the consumer's inclusive value for choosing all listings other than j as $\omega_{j\tau t}$ (Pan and Wang, 2021), which represents the set of alternatives that competes with listing j. Also, define $\pi_{j\tau t}$ as the static flow profit of listing j if night τ is booked in month t:

$$\pi_{j\tau t}\left(p, \omega_{j\tau t}\right) = q_{j\tau t}\left(p, \omega_{j\tau t}\right) \cdot \left(p \cdot (1-f) - c_j\right), \tag{12}$$

where $f = 0.03$ is the percent platform fee for sellers and c_j is the marginal cost per night. In what follows, I characterize the two pricing types in order.

Dynamic pricing with rigidity constraints. I start by characterizing the first pricing type: optimal nightly prices that are determined by a finite-horizon dynamic-pricing problem whereby the seller faces rigidity constraints. I assume sellers draw a chance to set prices with probability μ_j, following the classical Calvo (1983) model of price rigidiity. Thus, *observed* price path follows

$$p^{\text{dynamic}}_{j\tau t} = \begin{cases} p^*_{j\tau t} & \text{probability } \mu_j \\ p^{\text{dynamic}}_{j\tau, t-1} & \text{probability } 1-\mu_j \end{cases}, \tag{13}$$

where $p^*_{j\tau t}$ is the optimal price when the seller has the opportunity to re-optimize prices (with probability μ_j), and $p^{\text{dynamic}}_{j\tau t}$ is the observed prices. I assume sellers hold rational expectations on the trajectory of residual demand (driven by the market structure) and opportunity costs, as well as the possibility that they might not adjust prices in some future periods. Therefore, if the seller draws an opportunity to re-optimize prices, she solves for the dynamically optimal p^* by,

$$\max_{p} \pi_{j\tau t}\left(p, \omega_{j\tau t}\right) + \left(1 - q_{jt\tau}\left(p, \omega_{j\tau t}\right)\right) \mathbb{E}\left[V_{j\tau,t+1}\left(p, \omega_{j\tau,t+1}\right) | p, \omega_{j\tau t}\right]; \tag{14}$$

that is, the seller balances current profit $\pi_{j\tau t}\left(p, \omega_{j\tau t}\right)$, which depends on the probability that night τ can be rented out now, and future value $V_{j\tau,t+1}$, which is multiplied by the probability that night τ remains on the market. The value $V_{j\tau,t+1}$, and thus optimal dynamic price $p^*_{j\tau t}$, can be solved via backward induction. The details (including an illustrative example) are presented in Appendix C.3.

Several properties of this structure warrant discussions. First, $V_{j\tau,t+1}$ gives an "option value" for selling night τ in the future, which decreases with lead time $\tau - t$ in expectation. Second, competition enters indirectly through the inclusive value $\omega_{j\tau t}$ (the expected maximum utility if the consumer does not book listing j). Sellers know the current $\omega_{j\tau t}$ and form rational expectations about future $\omega_{j\tau t'}$ for $t' > t$. I assume sellers take the predicted $\omega_{j\tau t'}$ using information up to t, or $\mathbb{E}_t\left[\omega_{j\tau t'}\right]$.[19] The average number of available listings in a zip code is 61 (median is 48). With many sellers in the market, the model focuses on each seller's optimization over its *residual* demand. Lastly, I assume away multi-product pricing (which would have significantly complicated the model). Given the large choice sets and that no seller holds a sizable portion of the market, substitution within a seller can be safely ignored.

Non-dynamic pricing with uniformity constraints. I now move to the second pricing type: non-dynamic pricing with uniformity constraints. I assume that these sellers cannot adjust prices over time ($\mu_j = 0$). In addition, their flexibility of prices are limited across nights, so they no longer set prices independently for each night like the first type. Specifically, assume that listing j in quarter q draws the number of distinct "price bins" from a Poisson distribution, $K_{jq(\tau)} \sim Poiss\left(\rho_j\right)$. Given K_{jq}, the listing divides all nights in the quarter into $1 \leq K_{jq} \leq 90$ bins and sets one price for each bin, where each bin includes consecutive nights. A low ρ_j indicates a strong uniformity constraint where the listing tends to use pricing policies with few price points, with limited abilities to reflect nightly demand shifters in prices.

For tractability, I further assume that given K, the listing will partition the quarter into K clusters

[19] Specifically, for each seller segment l (introduced later), I estimate

$$\omega_{j\tau t'} = b_{0l} + b_{1l} \cdot t + b_{2l} \cdot t^2 + b_{3l} \cdot \omega_{j\tau t} + \Delta\omega_{j\tau t'}$$

and take the prediction, $\mathbb{E}_t\left[\omega_{j\tau t'}\right]$, to approximate seller expectations. In past versions, I also assumed perfect foresight and second-order Markov beliefs, and find similar estimates between these assumptions.

of consecutive nights based on underlying differences in the average consumer arrival rates $\bar{\lambda}_{j\tau}$. Then, it will set one price for each partition $\tau \in \left(\bar{\tau}^{k-1}, \bar{\tau}^{k}\right]$. Therefore, given the K bins, one can write the pricing problem as one that maximizes the expected profit for each partition:

$$\bar{p}_j^k(K) = \max_p \sum_{\tau=\bar{\tau}^{k-1}+1}^{\bar{\tau}^k} \left(p - c_j\right) \cdot \mathbb{E}\left[\text{occupancy}_{j\tau}(p)\right]. \tag{15}$$

The notation $p_j^k(K)$ implicitly ackowledges the partition-specific prices and the exact partitions $(\bar{\tau}^{k-1}, \bar{\tau}^k]$ change with K. Finally, integrating over the distribution of K, one can summarize the listing's optimal non-dynamic prices as

$$\bar{p}_{j\tau}^{\text{non-dynm}} = \mathbb{E}\left[\bar{p}_j^{k(\tau)} | \rho_j\right]. \tag{16}$$

Observed prices as a mixture of the two types. I characterize the observed prices of listing j as a weighted average between the optimal dynamic price $p_{j\tau t}^{\text{dynamic}}$ and the optimal non-dynamic prices $\bar{p}_{j\tau}^{\text{non-dynm}}$,

$$p_{j\tau t} = \theta_j p_{j\tau t}^{\text{dynamic}} + \left(1 - \theta_j\right) \bar{p}_{j\tau}^{\text{non-dynm}}. \tag{17}$$

Here, $\theta_j \to 1$ (0) will indicate that listing j is the type that sets dynamic (non-dynamic) prices. Whereas it is difficult to interpret a θ_j in-between 0 and 1 as a fixed seller type, I will later show that many listings have θ_j's close to either 0 or 1.

Identification through an example. Which moments in the data identify sellers' price-changing probability (μ_j), number of price points (ρ_j), and their (dynamic or non-dynamic) type (θ_j)? I illustrate identification using an example of one listing. Fixing demand at the estimated value and marginal costs at zero, I compute the model-implied prices over time and across nights under different values of $\left(\mu_j, \rho_j, \theta_j\right)$ and illustrate that the different parameters map into very different pricing behavior.

First, assume the listing fully optimizes its prices without any frictions ($\theta_j = 1$, $\mu_j = 1$). The right-most panel in Figure 5 (A) presents the distribution of these "frictionless" prices across nights and over the lead time. The solid line represents median prices in a given month relative to check-in, and the dashed lines are the 5th and 95th percentiles across nights. The corresponding (right-most) panel in Figure 5 (B) shows the last-month price for each night of the quarter. Last-month prices vary significantly across nights, ranging between \$70 and \$210 depending on the listing's residual demand for that night—almost three times between the minimum and the maximum. Moreover, prices of a given night vary significantly over the lead time. The median price starts around \$110 and goes down as the check-in date approaches, due to the decreasing op-

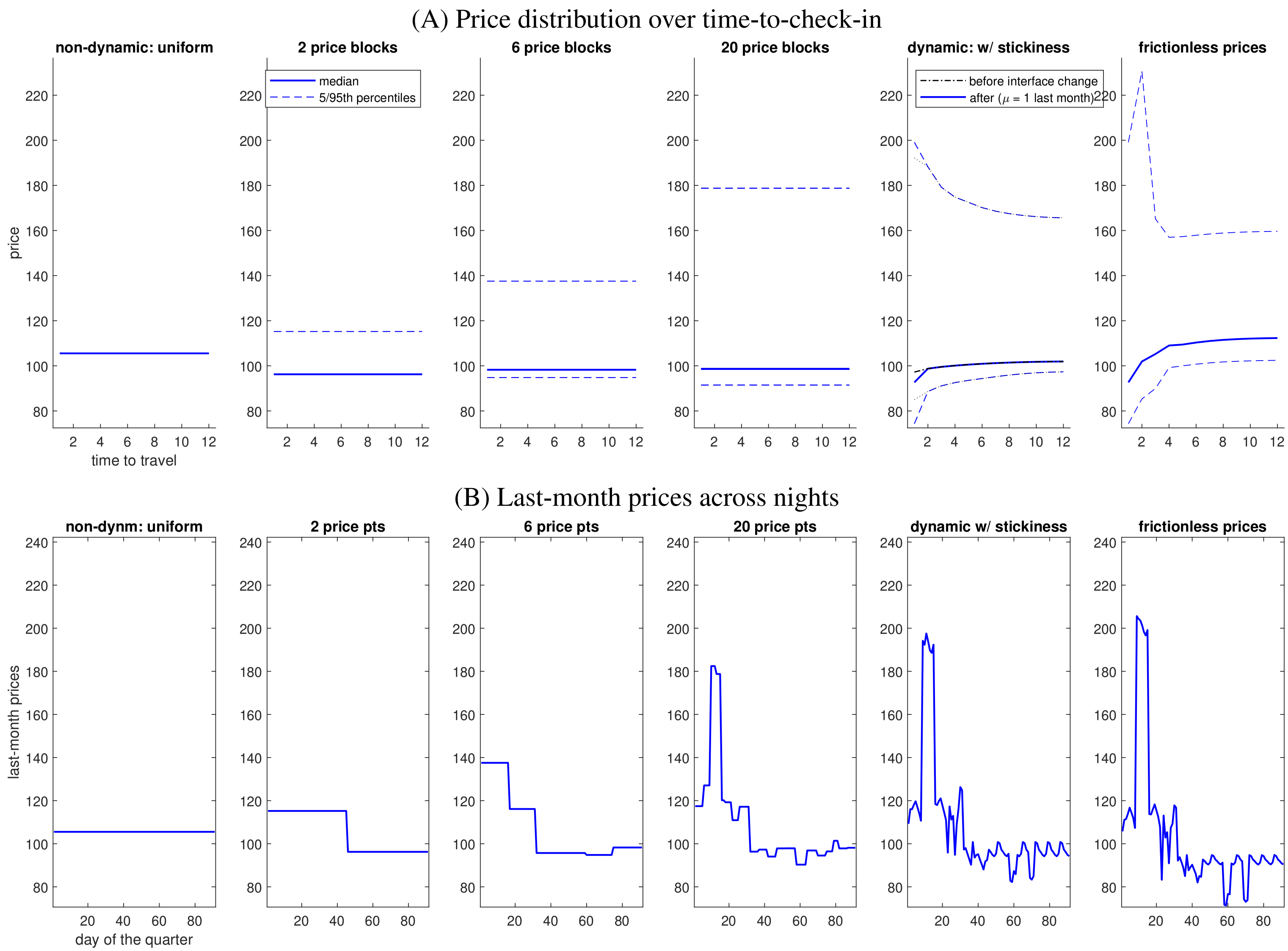


Figure 5: Price variation over time and across nights: A numerical example

Notes: A stylized example that demonstrates identification of supply-side parameters. All panels take demand for the same listing as given and assume zero marginal costs. The top panel focuses on price variations over time-to-check-in, whereas the bottom presents last-month prices across different nights.

portunity to sell. However, prices for highly sought-after nights increase to over $220 one month before check-in, due to the competitors gradually selling out and thus rising residual demand. Whereas this pricing-policy function is optimal, it is clearly demanding in the seller's ability to make sophisticated pricing decisions.

I then add the rigidity constraints, setting the inaction probability at $\mu_j = 0.25$. That is, the listing can only re-optimize prices in about one-fourth of the months. Shown in the second panel to the right, prices follow the dash-dot line. The price rigidity smooths out the optimal price variation over time: the seller does not adjust prices (when she should) in some periods, and when she can re-optimize prices, her prices preemptively accounts for her to future inactions. Therefore, the degree of price variation over time identifies μ_j.

Next, I examine the sellers who are incapable of adjusting prices over time, and in addition, face flexibility constraints. That is, I set $\theta_j = 0$ and vary the degree of flexibility constraints by changing K.[20] The first four panels from the left of Figure 5 show four examples of non-dynamic prices: a complex scheme with 20 different nightly prices, and less flexible pricing schemes with six, two, and one price. Sellers who can set many price points will be able to capture most of the nightly demand variation, despite not being able to adjust prices over time. Conversely, sellers who cannot set many price points will set inflexible nightly prices, with many contiguous nights "lumped together." The degree of flexibility across nights identifies ρ_j.

The above identification arguments do not distinguish between two "knife-edge" cases: one where the listing is the dynamic pricing type ($\theta_j = 1$) but faces full rigidity constraints ($\mu_j = 0$), and another where the listing is the non-dynamic pricing type ($\theta_j = 0$) but does not face flexibility constraints (ρ_j is very large). To separate these two types of listings, I leverage sellers' heterogeneous responses to the 2019 launch of "last-minute discount" in the pricing interface. I assume that this new feature allows dynamic-pricing sellers to adjust prices once in the last month before check-in, regardless of the value of μ_j,[21] but it will not affect non-dynamic pricing sellers' behavior. In the above example, last-minute discount will affect the last-month prices for listings in the fifth panel (where $\theta_j = 1$ and $\mu_j < 1$), but not listings in other panels (either those with $\theta_j = 0$ or with $\theta_j = 1$ and $\mu_j = 1$). In other words, this extra moment draws the line between listings who would never engage in dynamic pricing and those who would engage in some dynamic pricing but face significant price rigidity constraint.

Estimation. I follow Pan and Wang (2021) to cluster all listings into segments based on their observed characteristics and observed actions. The underlying idea is similar to Bonhomme et al.

[20] I should change ρ_j according to the model. But changing K (the realized number of prices) serves as a better illustration.

[21] I assume sellers set last-minute discounts in the last month, which is a simplifying assumption, but it agrees with the pattern shown in Figure B.1.

(2019), who show such ex-ante clustering can approximate a model with continuously distributed persistent heterogeneity with a flexible distribution. This method suits my paper because it does not impose strong shape restrictions on the joint distribution of seller parameters.

I cluster all listings into 150 groups by prices and characteristics. For each listing j, I first obtain its demand intercept, the number of listings operated by the owner, the listing's median price, the price discount in the last two months before check-in, and the difference in its last-month discount after and before the 2019 interface change. Demand and the number of listings are important characteristics to control for. The vector of price moments closely resembles my identification arguments (which is important for the ex-ante split segments to resemble the underlying heterogeneity; see Bonhomme et al., 2019). I then use hierarchical clustering to group all listings into 150 clusters.

For cluster l, I estimate c_l, μ_l, and θ_l using a generalized methods of moment (GMM) approach. I match the following moments for each cluster l: (1) the median price conditional on months-to-check-in (m_{1l}, a 12×1 vector), (2) median changes in last month's price before and after 2019 (m_{2l}, a scalar), and (3) the median interquartile range of price across weekday nights within the last month (m_{3l}, a scalar). The choice of moments directly follows my identification strategy above.[22] After estimation, I compute asymptotic standard errors from the variance-covariance matrix (Hansen, 1982).

4.3 Quarterly participation decisions

Potential seller exit limits the platform's ability to adopt a market design unfavorable to sellers. I capture this force using a static entry/exit model. Recall that $q_{j\tau t}$ denotes the probability that listing j for night τ is booked by any customer in month t. The expected total profit for quarter q is the sum of expected profit for each night τ in that quarter,[23]

$$\Pi_{jq} = \mathbb{E}\left[\sum_{\tau \in q} \underbrace{\sum_{t=1}^{12}\left(\prod_{\iota=1}^{t-1}(1-q_{j\tau\iota})\right) q_{j\tau t}}_{\text{prob. rented in any of the 12 months}} \cdot \underbrace{(p_{j\tau t}\cdot(1-f)-c_j)}_{\text{markup after platform fee}}\right]. \tag{18}$$

I estimate the fixed costs using maximum likelihood, assuming a listing stays in the market

[22] The one-step GMM minimizes $(m_{1l}, m_{2l}, m_{3l})' I_{14} (m_{1l}, m_{2l}, m_{3l})$, where I_{14} are identity weights.

[23] To estimate the profit for listings that do not currently operate on the market, one needs to infer the demand intercept $\hat{\delta}_{jq}$ had it operated in the market. For observed listing-quarters, I estimate

$$\delta_{jq} = \delta_j^1 + \delta_q^2 + \Delta\delta_{jq}$$

and project $\hat{\delta}_{jq} = \hat{\delta}_j^1 + \hat{\delta}_q^2$. The R-squared of the above equation is 0.993. The projected δ's are only used to estimate fixed costs.

(conditional on having entered the market) if it earns positive net expected profit:

$$\Pi_{jq} - F_{jq} > 0. \tag{19}$$

Here, fixed costs F_{jq} is the opportunity cost of participating in Airbnb for the quarter. I parameterize this cost as

$$F_{jq} = \bar{F}_{l(j)} + \psi_1 \mathbb{I}_{\text{post regulation}} + \psi_2 \text{dist}_j + \psi_3 \text{dist}_j^2 + \psi_4 \zeta_{jq}, \tag{20}$$

where $\bar{F}_{l(j)}$ is segment l's fixed cost. $\mathbb{I}_{\text{post regulation}}$ is an indicator for the 2018 San Francisco regulation, which imposes a mandatory license requirement with an annual fee (and an application process). dist_j characterizes the listing's distance to Union Square (in miles) and proxies for the higher forgone rent in downtown San Francisco. ζ_{jq} is a type-1 extreme-value error term, which implies a binary-logit choice probability for the participation decision.

5 Estimation results

Demand estimates. Table 2 presents demand estimates. I find segment 2 (arriving closer to the check-in date) is less price sensitive than segment 1.[24] The residual from the control function, $\eta_{j\tau t}$, has a sizable coefficient, suggesting that prices are endogenous to demand shocks.

The average price elasticity in San Francisco is -2.51. This average elasticity is consistent with Jeziorski and Michelidaki (2019), who use experimental variation to estimate the price coefficient for Airbnb in San Francisco. This similarity gives face validity to the control-function approach. Further, the estimated day-of-week fixed effects suggest a modest weekend demand surge for both segments. The month-of-the-year fixed effects reflect strong seasonality in the number and composition of potential consumers.

These arrival parameters are visualized in Figure 6, which shows the implied segment-specific arrival rate by time-to-check-in, day of the week, and month of the year, and the corresponding data moments and model fit. The model predictions matche with the observed sales outcomes across all three dimensions. These rich demand variations, over time and across different nights, will be important drivers of *optimal* prices—ones that a rational, frictionless seller should set.

Marginal costs and fixed costs. Figure 7 summarizes the distribution of marginal and fixed costs across listings. Recall that supply-side parameters are separately estimated for all 150 segments.

The medain marginal cost is \$38 per night (the average is \$60), comparable to San Francisco's average wage (\$36 an hour in 2019). These costs reflect the time to clean the property and com-

[24]The price-sensitivity difference is consistent with the myopic consumer assumption; if consumers were to wait for discounts, late adopters should be more price sensitive.

Table 2: Demand parameter estimates

	Segment 1	std err	Segment 2	std err
log(price)	-3.144	0.010	-2.393	0.006
#customers: baseline (last month)	1.000		2.366	0.022
%Δ by months to check-in	-0.389	0.001	-1.567	0.005
%Δ on holidays	0.202	0.011	-0.048	0.017
%Δ February	-0.224	0.006	0.581	0.006
%Δ March	0.090	0.006	0.848	0.007
%Δ May	0.195	0.005	0.374	0.008
%Δ June	0.536	0.005	0.226	0.009
%Δ August	0.313	0.005	-0.346	0.011
%Δ September	0.263	0.005	-0.104	0.009
%Δ November	-0.244	0.006	-0.281	0.007
%Δ December	-0.412	0.006	-0.296	0.007
%Δ Monday	-0.004	0.004	-0.063	0.007
%Δ Tuesday	-0.007	0.005	-0.026	0.007
%Δ Wednesday	-0.003	0.005	0.044	0.007
%Δ Thursday	0.018	0.005	0.096	0.007
%Δ Friday	0.165	0.005	0.204	0.007
%Δ Saturday	0.164	0.005	0.229	0.007
scale of price residual (control fn)	2.561	0.008		
scale of price residual squared	-0.205	0.010		

Notes: Nonlinear parameters from the demand model. Implied δ_{jq}'s are not reported in the table. Number of observations = 16,674,620 (33,354 listing-quarter × 91 check-in days × 12 months = 36,422,568, but only 16.7 million observations are when the listing is available). Log likelihood at convergence = -3,503,185. Asymptotic standard errors computed from the inverse Hessian matrix.

municate with guests, but might also amortize the property's depreciation. Marginal costs are heterogeneous across sellers, with an interquartile range of [$24, $68], suggesting different sellers might have different hassle of operating on Airbnb. These costs push prices above the revenue-maximizing level and to different optimal levels for different sellers.

The monthly fixed cost is $5,540 for an average listing in downtown San Francisco. Listings farther away from downtown have lower fixed costs; for example, three miles away from Union Square, the average monthly fixed cost is $2,100 (see Appendix Table E.1). These costs are comparable to San Francisco's monthly rent in the sample period.[25]

Cognitive constraints – rigidity and uniformity constraints. Figure 8 summarizes the distribution of listings' propensity to use non-dynamic pricing (θ) and price-setting costs (μ and ρ).

[25] For example, the city's average rent in 2018-2019 is about $3,500. Source: https://sf.curbed.com/2019/10/2/20895578/san-francisco-median-rents-market-census-september-2019. Accessed in May 2021.

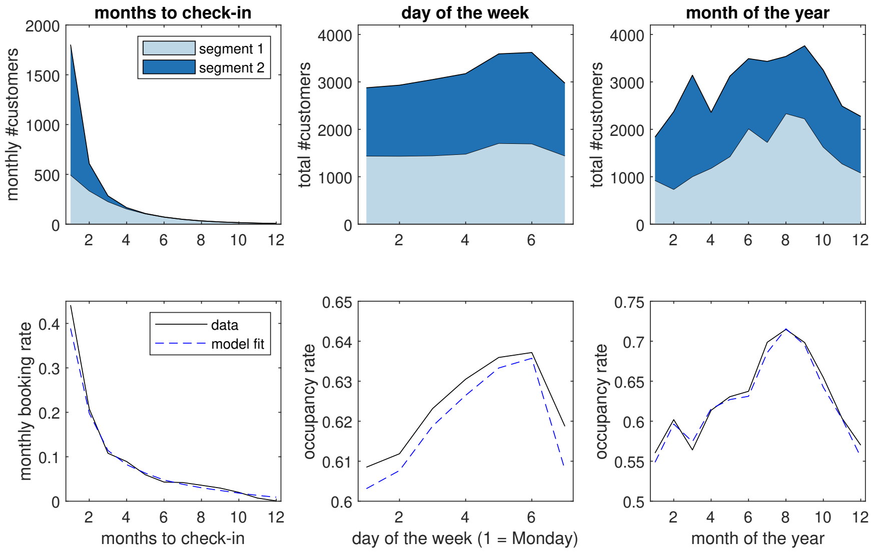


Figure 6: Customer arrival: model estimates and fit

Notes: Top panels: implied average *monthly* arrival rate for the two segments over time-until-check-in (left), and the *total* number of customers over day of the week (middle) and month of the year (right). Right: empirical and model-implied booking rate (left), which is defined as the probability of being booked in a given month conditional on availability, and occupancy rate (middle and right), which is defined as the probability of a given night ever being booked.

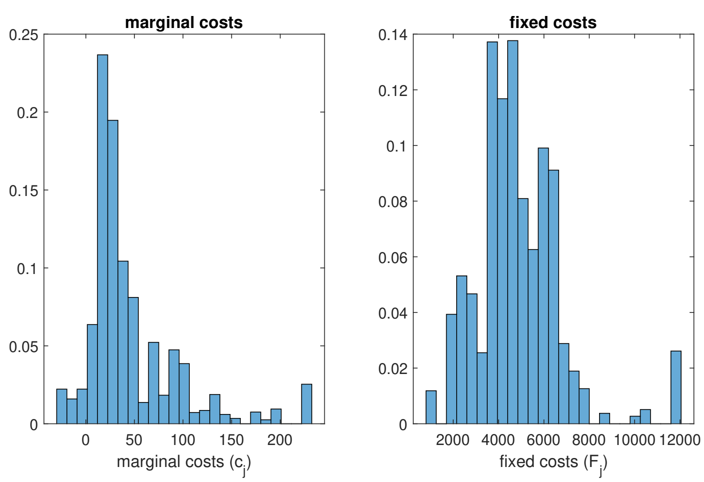


Figure 7: Distribution of marginal costs and fixed costs

Notes: Marginal distribution of nightly marginal costs and monthly fixed costs. Both distributions are winsorized at the 98th percentile.

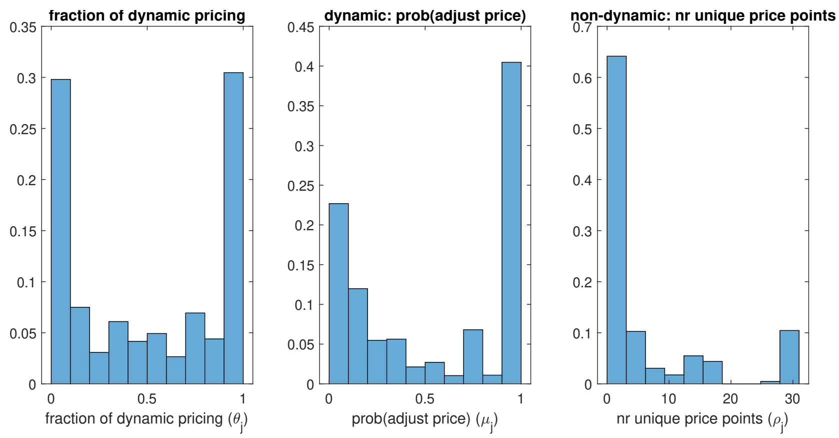


Figure 8: Distribution of price-friction parameters

Notes: Marginal distribution of demand intercept (quality), marginal costs, probability of changing prices, fraction of sellers using dynamic pricing strategies, fraction using non-uniform pricing strategies, and quarterly fixed costs.

First, the left panel presents the distribution of θ_j. 48% listings have $\theta_j > 0.5$ (and for most of them, $\theta_j \to 1$), meaning they can set prices independently for each night and, in addition, might be able to adjust prices over time. The rest of listings have $\theta_j \leq 0.5$ (and for most of them, $\theta_j \to 0$), suggesting that they are unable to adjust prices and, in addition, might face uniformity constraints. I now examine these two groups of sellers in turn.

For listings of the dynamic type (with $\theta_j > 0.5$), the middle panel presents the distribution of μ_j, the listing's probability of adjusting prices in each month. μ_j is clearly bi-modal. 41% of listings always adjust prices, and 23% never adjust prices before the last-minute discount feature was available (and start using the feature after it was introduced). The remaining 36% only get to change prices in some months, and most change prices rarely. So, although there is a small set of sellers who set virtually frictionless prices,[26] most of the listings who are capable of some dynamic pricing still face significant rigidity constraints.

For listings of the non-dynamic type (with $\theta_j \leq 0.5$), the right panel characterizes the distribution of ρ_j, the expected number of price bins sellers can charge for each quarter. The average of ρ_j is 5.3. 74% of listings can set five or fewer price points in expectation. The low ρ_j suggests that half of the listings, who already cannot set dynamic prices, also face strong uniform frictions that lead to the use of very simple pricing policies.

Correlation with observed characteristics. I further project each estimated supply-side parameters on observed characteristics to examine what explains differences in pricing strategies. Con-

[26] One can interpret these "frictionless" listings as using some form of pricing algorithm. Incidentally, they happen to capture 41% $\times$ 48% $=$ 20% of the market, about equal the share of hosts who ever used Smart Pricing reported by (Foroughifar and Mehta, 2023) but likely higher than the stable share of hosts using the algorithm.

trolling for listing characteristics, the biggest difference between single- and multi-listing sellers is the extent of cognitive constraints, or whether the seller *can* set dynamic prices. One standard deviation in the number of listings explains 0.23 standard deviations of θ_j. In addition, one standard deviation in the number of listings explains 0.07 standard deviations of marginal costs, 0.11 standard deviations of ρ_j, and -0.01 standard deviations of μ_j. This result echoes the earlier finding that multi-listing sellers set sophisticated pricing strategies. See Appendix Table E.2 for detail.

6 Counterfactual

I start by comparing equilibrium outcomes under the factual scenario ("baseline") with the frictionless market outcome where all frictions are eliminated ("frictionless").Although the no friction scenario is *unattainable* in practice, it gives an upper-bound estimate of the potential gains from alleviating pricing frictions. Then, I examine two platform remedies. The first is one in which the platform enforces a revenue-maximizing pricing algorithm (which approximates "Smart Pricing," Airbnb's pricing algorithm). The second involves a more fundamental redesign of the platform: the platform provides a flexible price-adjustment function to sellers, and based on these functions, each seller sets one price and uses the platform-provided price adjustments. In this scenario, the platform leverages its informational and technological advantage and provides assistance to sellers, but it does not take away sellers' rights to set higher-than-revenue-maximizing prices. I compare profits and consumer surplus across the four scenarios. All calculations are based on the period from May 2015 to December 2017, the sample period before the San Francisco short-term rental regulation.

Counterfactual 0: A frictionless market. The first two columns of Table 3 compare the baseline with the frictionless marketplace, in which prices are set where all pricing frictions are eliminated (i.e., $\mu_j = 1$, $\theta_j = 1$, and ρ_j is irrelevant in this case). One standard deviation of the price (within listing, across nights) increases from 4% in the baseline to 6% in the frictionless market for the median listing. Also, frictionless prices generally decrease over time as the option value for waiting for additional customers dwindles. I show the percent last-month discount increases to 30% from 2% (i.e., almost completely sticky prices) for the median listing. These two aspects lead to lower last-month prices and higher occupancy rates.

I further explore who gains and who loses in the frictionless scenario. The median seller gains as net profits increase from \$2,350 to \$2,440 per quarter, or by 3.8%. Table 4 further presents the distribution of within-seller profit changes. 1% sellers lose because they do not face significant frictions but their competitors can now price more flexibly (and often lower). Still, most sellers gain from the removing the pricing frictions, and 5th/95th percentiles of the profit gain is [0%, 15%]. Other than sellers, consumers also gain as their surplus (measured in utils) increases by 14%. The platform obtains a modest revenue gain of 2.5%. Almost all market participants benefit from eliminating pricing frictions.

Table 3: Counterfactuals: median-seller outcomes, platform profit, and consumer surplus

	baseline	frictionless	full algo.	algo.-assist
last-month price	133.66	120.49	99.27	118.49
price dispersion across nights	0.04	0.06	0.09	0.06
last-month discount	-0.02	-0.30	-0.38	-0.29
occupancy rate	0.73	0.77	0.90	0.79
seller quarterly profit ($k)	2.35	2.44	2.13	2.42
seller participation rate	1.00	1.00	0.92	1.00
total platform revenue ($m)	2.36	2.42	2.40	2.42
average consumer surplus (util)	4.11	4.69	6.03	4.84

Notes: This table summarizes counterfactual market outcomes in the baseline, frictionless market, and under the two platform remedies. All seller-level outcomes (last-month price, price dispersion, last-month discount, occupancy rate, and profits) are at the median. Price dispersion is the standard deviation of log(price) across nights. Last-month discount is the ratio between last-month price and first-month price, minus one. Profit is the net quarterly profit after substacting fixed costs.

Table 4: Counterfactuals: within-seller profit changes relative to the baseline

	frictionless	full algo.	algo.-assist
fraction who earn negative profit	0.00	0.08	0.00
– who lose relative to baseline	0.01	0.56	0.09
– who gain relative to baseline	0.69	0.31	0.62
profit increase relative to baseline: 5%	-0.00	-1.00	-0.02
– 25%	0.00	-0.19	-0.00
– median	0.03	-0.02	0.02
– 75%	0.05	0.02	0.05
– 95%	0.15	0.08	0.14

Notes: This table summarizes within-seller changes in profit in the counterfactual scenarios (relative to the baseline scenario). Fraction who lose (gain) profit is defined as the fraction of sellers who earn less than 99% profit (more than 101% profit) relative to the baseline, where I put a 1% buffer to filter out sellers who are close to indifferent.

Remedy 1: Full price control by revenue-maximizing algorithm. Because the primary source of pricing frictions is sellers' cognitive constraints, I focus attention on the case where the platform leverages its data advantages to offer direct assistance in seller pricing. Other remedies, such as provision of information (such as Alibaba's training videos) or an easy-to-use pricing interface, are unlikely viable alternatives because, as I have documented, sellers do not learn to improve pricing and show little responses to the existing interface improvement. Therefore, I focus attention on the platform's use of pricing algorithms to directly assist seller pricing—either by full or by partial control of prices.

For the first platform remedy, I simulate the scenario where the platform enforces a listing-revenue-maximizing algorithm on every listing. To implement this counterfactual, I assume that each listing maximizes own total *revenue* but is not constrained by any frictions. From my conversation with practitioners, this hypothetical algorithm is similar to the existing "Smart Pricing" algorithm (Ye et al., 2018), except that in the counterfactual I assume the algorithm takes full control of all prices.

Column 3 of Table 3 shows that prices are indeed highly variable under the algorithm's control. But because the revenue-maximizing algorithm does not factor in seller marginal costs, prices are also much lower—they are 26% below the baseline and 18% below the frictionless scenario. As a result, the occupancy rate jumps up to 90%, consumer surplus improve beyond the frictionless scenario, and platform total revenue is 1.7% above the baseline (although it is below the frictionless scenario). However, seller profits are significantly lower because many of them have high marginal costs, which the algorithm does not account for. The median seller now earns only $2,160 per quarter, down by 11% from the frictionless scenario (and 8% from the baseline). Further, Table 4 shows 8% of sellers now earn negative profits and will exit the platform, and 56% of sellers are worse off than the baseline.

Therefore, whereas the full price control using a revenue-maximizing algorithm does make prices more flexible, its main effect seems to be to decrease the overall price level. The lower prices are closer to revenue-maximizing, which improve consumer surplus and the platform's payoff, although at a steep cost of seller profits. The high seller exit rate does limit the platform gain in this counterfactual and might have an averse long-run impact not captured by the model. The negative seller impact from this counterfactual also echoes sellers' resistence to the existing Smart Pricing algorithm, which, upon seller opt-in, takes full price control and is often reported to set prices much lower than what the seller would like.[27]

Remedy 2: Algorithmic price adjustments around seller-determined base prices. The above analysis suggests that a possible improved platform design is to leverage the algorithm's ability to adjust prices following variations in opportunity costs or demand shifters, but leave it on sellers to determine the base price to reflect their marginal costs. I now simulate such a platform design,

[27]The counterfactual findings are also consistent with a recent paper by Filippas et al. (2021), who observe that, when a rental-car platform enforces a revenue-driven pricing algorithm to everyone, more than 30% sellers exit the platform.

in which the platform commits to not influence sellers' preferred price *level* but still uses the algorithm to determine the *shape* of the pricing policy function.

Specifically, the platform redesigns pricing into two stages. In the first stage, the platform presents a price-adjustment function, $a_{ml\tau t}$, for market m, listing type $l(j) = 1, ..., 150$, night-of-the-quarter τ, and time t (with time-to-checkin $\tau - t$). The platform announces that the consumer price will be

$$p_{j\tau t} = \bar{p}_{jq(t)} \times \left(1 + a_{ml(j)\tau t}\right) \tag{21}$$

and that sellers only set quarterly price $\bar{p}_{jq(t)}$. In the second stage, sellers observe the now-committed $a_{ml\tau t}$ and set $\bar{p}_{jq(t)}$. I assume sellers are able to set $\bar{p}_{jq(t)}$ because this task is within even the most stringent cognitive constraint. [28]

What would the new equilibrium look like, and how far are we from the first best? The last column of Table 3 and 4 present the results. First, I find that the median price level is close to (but a bit lower than) the first best and that the degree of price adjustments over time, price dispersion, and occupancy rate are almost identical to the first best. On the aggregate, the platform's new price function mimicks that of the first best and forges the "shape" of equilibrium prices. As a result of this similarity, consumer surplus is now 3.2% above the frictionless scenario (due to the slightly lower prices) and is much higher than the baseline scenario. Sellers, on the other hand, mostly gain from this change. The median seller profit is 3.0% higher than the baseline. 62% of sellers gain from this change, and 9% of sellers lose. Virtually no seller chooses to exit. All in all, the crude platform-assisted pricing scheme helps consumers and most sellers, and it also simplifies seller decision-making and loads most of the decision burden to the platform.

7 Summary

Pricing in a complex environment is difficult for individual sellers. While providing aid to seller pricing, the platform might have incentives to steer prices toward its objective. This paper shows seller-pricing frictions are prevalent on Airbnb. Two mechanisms drive the frictions: sellers' price-setting costs and cognitive constraints. This paper estimates that pricing frictions lead to a 14% consumer welfare loss and a 0%-15% profit losses for sellers. Given the loss, can the platform ameliorate the frictions in any way? Based on the estimates, a flexible pricing interface alone is ineffective because significant frictions come from sellers' cognitive constraints (instead of price-

[28] To implement this counterfactual, for each j-τ-t, I take the ratio between the first-best prices over the counterfactual uniform (and time-invariant) prices to compute $\tilde{a}_{j\tau t}$. Then, I average these a's for each market m, time t, and for each type l to get $a_{ml\tau t}$. One might imagine $a_{ml\tau t}$'s can be crude if the groups l are crude. One might also imagine $a_{ml\tau t}$'s can be further optimized by the platform. For this counterfactual exercise, I use the crude (and potentially suboptimal) $a_{ml\tau t}$'s to illustrate that improvements can still be gained. Letting the platform strategically choose a's will introduce an enormous computational burden and thus is beyond this paper.

setting costs). Enforcing a revenue-maximizing algorithm will also see limited return, because such an algorithm does not internalize sellers' marginal costs, which is driving the incentive conflict between sellers and the platform. However, I show that a simple market design, which leverages the platform's information and technological advantage but still gives sellers important decision rights, will eliminate almost all frictions and improve market outcomes. Ameliorating the pricing frictions is feasible with the "right" market design.

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Online Appendix

A Sampling and interpolation details

Sample selection. I focus on Airbnb listings in San Francisco and take a subsample based on three criteria. First, I condition on listings that require a minimum stay of less than three nights to eliminate weekly and long-term rental listings.[29] Second, I focus on the most popular listing types: private rooms (38% of all listings in San Francisco), studios and single-bedroom apartments (31%), and two-bedroom apartments (17%). Lastly, I condition on listing-years when the seller blocks no more than a quarter of nights. 25% of listings are dropped from this step, which I interpret as part-time sellers (whose incentives differ from full-time sellers).[30] These sample-selection criteria lead to the main sample described in section 2.

Interpolation of prices. I do not observe the price of the nights that are booked. Fortunately, most prices do not vary much over time or are characterized by simple price-policy functions, making interpolating the missing prices feasible.

In the raw data (at the listing-night-sampling-date level), 13.5% of price observations are missing. I start with the set of listings that charge uniform prices, that is, the same price across all nights for a given sampling date. For listings with uniform prices, I interpolate all missing prices using this uniform price.[31] This step fills in 3.9% of observations, which is 29% of all missing prices.

Next, I find observations for which all nights' prices can be characterized by the base price plus a fixed weekend surcharge. Such observations account for 8% of missing prices, and I fill in missing prices using the observed, stylized pricing policy. Similarly, I also fill in prices that vary by calendar month of the night plus a weekend surcharge (11% missing prices) and weekly prices plus a weekend surcharge (2% missing prices). At this point, half of the missing prices have been interpolated.

Further, I examine intertemporal variation in prices for the given night. Specifically, I examine nights for which prices do not vary at all. I find that an additional 15% of missing prices fall into this category, in which case, I interpolate the price of the night by the constant, observed prices.

By this step, 35% of the original missing-price data are still missing. I now take a stronger stance and assume missing prices are equal to the last-observed prices. This step fills in 19% of

[29] On the platform, 67% of listings require a minimum stay of no more than 3 nights, 11% require a minimum stay of between 4 and 7 nights, 1% require between 8 and 29 nights, and 21% require more than 30 nights. Requiring a minimum stay of more than 30 nights will put the listing in the long-term rental market and exempt it from the hotel-lodging tax and other regulations.

[30] Of the remaining listings, 75% are available for at least 305 nights out of a year, and 50% are available all year.

[31] In practice, I allow for a 0.5% standard deviation in unexplained price differences, to accommodate the possibility of a scraper error. This threshold is below $1 at the median price so can be safely ignored.

missing prices, or 2.7% of all price data.

Interpolation of occupancy. Occupancy could be under-measured because some nights are last-observed weeks before the stay date, during which time it might be booked, but the booking might not be observed. I leverage the fact that some nights are on (or close to) the last sampling date and are not subject to the truncation problem. As such, I interpolate the occupancy rate by matching each night with an observationally similar night close to the sampling date. To do so, I assume the expected occupancy rate is the same up to observed characteristics of the date, such as weekday or month of the year. However, observed occupancy is different because of the difference in truncation. Given this assumption, I estimate a simple linear regression of binary occupancy for listing j night τ as a function of the degree of truncation (the number of days between the last observation and τ) interacted with month of the year and weekday of τ:

$$\text{occupancy}_{j\tau} = f\left(\text{truncation}_{j\tau}, \tau\right) + \varepsilon_{j\tau}. \tag{22}$$

I parameterize function f by quadratic specifications of $\text{truncation}_{j\tau}$ interacted with a fully saturated set of fixed effects.

The estimated $\hat{f}$ predicts, given night τ, the expected occupancy if truncation becomes zero. Denote this difference as $\Delta\text{occupancy}_{j\tau}$. I find that if the night is truncated by two weeks, the occupancy rate is predicted to be 5 pp. higher, or 8% relative to the observed (truncated) occupancy rate at 0.66. In the extreme, if the night is truncated by 30 days, the occupancy rate is predicted to be 11 pp. higher. Across all dates, the occupancy rate would have been 0.70 in the absence of truncation, so the interpolation leads to a 4 pp. increase in measured occupancy rate. Lastly, for nights that are not occupied by my last observation, I sample binary outcomes from $\Delta\text{occupancy}_{j\tau}$, which is interpreted as "additional occupancy events" in the absence of truncation. I draw additional occupancy events from this probability.

B Additional descriptive evidence

B.1 Across-seller and within-seller price variability

I present the full tables corresponding to Figures 3 and 4. Table B.1 (A) shows parameter estimates of equation (3), where I compare different measures of price variation across sellers who operate different number of listings on the platform. Table B.1 (B) presents estimates of equation (4), which adds seller fixed effects. Table B.2 (A) and (B) further present estimates of equations (5) and (6), which examine how the price variability changes by seller tenure and calendar year.

Appendix Table B.1: Pricing-strategy differences by sellers' number of listings

(A) *Across*-seller differences (without seller FEs)

	Dependent variable:		
	std of %prices	%last-month discount	%summer premium
	(1)	(2)	(3)
2 listings	0.011***	−0.014**	0.004*
	(0.003)	(0.005)	(0.002)
3-5 listings	0.023***	−0.036***	0.016***
	(0.004)	(0.007)	(0.003)
6+ listings	0.064***	−0.021	0.021**
	(0.015)	(0.018)	(0.009)
baseline (single-listing)	0.067	-0.044	0.019
seller FE	no	no	no
loc.-time/type and amenities FE	yes	yes	yes
Observations	71,565	70,686	70,594
R^2	0.413	0.393	0.399

Note: *p<0.1; **p<0.05; ***p<0.01

(B) *Within*-seller changes (with seller FEs)

	Dependent variable:		
	std of %prices	%last-month discount	%summer premium
	(1)	(2)	(3)
2 listings	−0.0001	0.004	−0.006**
	(0.003)	(0.005)	(0.003)
3-5 listings	0.001	0.005	0.001
	(0.004)	(0.007)	(0.004)
6+ listings	0.020**	−0.003	−0.0002
	(0.008)	(0.011)	(0.010)
seller FE	yes	yes	yes
loc.-time/type and amenities FE	yes	yes	yes
Observations	71,565	70,686	70,594
R^2	0.746	0.820	0.727

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Baseline Y is the conditional mean of the dependent variable for single-listing sellers. Panel A focuses on differences between sellers with different #listings. Panel B controls for seller fixed effects (FEs), focusing on within-seller changes in #listings. Standard errors are clustered at the seller level.

Appendix Table B.2: Pricing-strategy differences by seller tenure and year

(A) Changes by tenure (with seller FEs)

	Dependent variable:		
	std of %prices	%last-month discount	%summer premium
	(1)	(2)	(3)
1 year tenure	-0.003	0.007	0.013^{***}
	(0.003)	(0.005)	(0.005)
2 years	-0.004	0.0003	0.008
	(0.004)	(0.008)	(0.006)
3 years	-0.005	0.005	0.011^{*}
	(0.005)	(0.010)	(0.007)
4+ years	-0.010	0.010	0.008
	(0.006)	(0.012)	(0.007)
baseline (0 years tenure)	0.088	-0.071	0.021
seller FE	yes	yes	yes
loc.-time/type and amenities FE	yes	yes	yes
Observations	91,390	90,169	90,139
R^2	0.735	0.732	0.701
Note:			*p<0.1; **p<0.05; ***p<0.01

(B) Changes by calendar year (with seller FEs)

	Dependent variable:		
	std of %prices	%last-month discount	%summer premium
	(1)	(2)	(3)
year 2017	0.001	-0.004	0.002
	(0.001)	(0.003)	(0.002)
2018	0.002	0.006	0.010^{***}
	(0.002)	(0.005)	(0.002)
2019-20	0.009^{***}	-0.026^{***}	-0.002
	(0.003)	(0.007)	(0.003)
baseline (2015-16)	0.066	-0.036	0.019
seller FE	yes	yes	yes
loc.-type and amenities FE	yes	yes	yes
Observations	91,486	90,265	90,234
R^2	0.712	0.701	0.678
Note:			*p<0.1; **p<0.05; ***p<0.01

Notes: Baseline Y is the conditional mean of the dependent variable for sellers with 0 years of tenure (panel A) or for the year 2015-16 (panel B). Standard errors are clustered at the seller level.

B.2 Multi-listing sellers are more responsive to demand shifters

Given that multi-listing sellers set more flexible prices, a natural follow-up question arises: Can their prices capture demand shifters better, or is it that they face different demand in the first place? To answer this question, I collapse data to the level of listing (j) and nights (τ) and regress the occupancy rate on *salient* characteristics of the night, such as the summer dummy (but also weekend and holidays) and the interaction between that and the log number of listings:

$$\text{occupancy}_{j\tau} = \alpha \log\left(\text{price}_{j\tau}\right) + \beta_1 \log\left(\#\text{listing}_{j\tau}\right) + \beta_2 \text{summer}_\tau + \beta_3 \log\left(\#\text{listing}_{j\tau}\right) \cdot \text{summer}_\tau + \delta_j + \lambda_{y(\tau)} + \varepsilon_{j\tau}. \tag{23}$$

I also control for the price, listing fixed effects, and calendar-year fixed effects. Equation (23) examines whether the occupancy rate is higher during the summer and whether this relationship differs across sellers with different scales.[32] The main parameter of interest is whether multi-listing sellers face the same summer-demand shifter, that is, to test against $\beta_3 = 0$. I also estimate a similar regression with log price as the dependent variable to test whether multi-listing sellers set different summer price premiums than single-listing sellers.[33]

Table B.1 finds that, conditional on price, the occupancy rate is 3 pp. higher during the summer, 2 pp. higher during the weekend, and 2 pp. lower during a public holiday.[34] In addition, multi-listing sellers do not face different demand shifters, because β_3 is indistinguishable from zero (except for summer, in which case, multi-listing hosts face a slightly smaller demand increase). Nevertheless, I reproduce the previous finding that multi-listing sellers set higher prices for the summer and weekends and lower prices for holidays. These results suggest multi-listing sellers face the same demand but can set different prices to capture demand. Hence, these results support the general picture that persistent seller differences create large degrees of heterogeneity in pricing strategies.

B.3 Additional evidence of sellers' reaction to the "last-minute" discount feature

Figure 4 (C) and Table B.2 (B) demonstrate that there is a modest difference in the extent of last-month discounts offered by sellers after 2019, when the platform launched the automated "last-

[32] As an aside, the capacity-constrained nature of the market makes optimal prices depend on the level of the occupancy rate (as opposed to only depending on the price elasticity). Holding elasticity fixed, the higher the occupancy rate, the more likely the listing will be rented out early at a given price, and the higher the optimal price should be.

[33] This exercise is related to Leisten (2020), who examines hotels' ability to price in college football games (a "non-salient" demand shifter) relative to their ability to price in salient shifters, and Huang et al. (2020), who examine supermarkets' ability to set prices that capture product-level idiosyncratic demand.

[34] The lower demand during holidays can potentially be explained by higher supply during holidays, reducing the residual demand for each listing.

Appendix Table B.1: Price dispersion across weekends, summer, and holidays

	Dependent variable:							
	occupancy	log(price)	occupancy	log(price)	occupancy	log(price)	occupancy	log(price)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(listing)	0.010^{***}	0.014^{***}	0.009^{***}	0.020^{***}	0.009^{***}	0.024^{***}	0.010^{***}	0.011^{***}
	(0.001)	(0.0005)	(0.001)	(0.0005)	(0.001)	(0.0005)	(0.001)	(0.0005)
log(price)	-0.104^{***}		-0.104^{***}		-0.097^{***}		-0.111^{***}	
	(0.002)		(0.002)		(0.002)		(0.002)	
summer quarter	0.033^{***}	0.027^{***}					0.033^{***}	0.027^{***}
	(0.001)	(0.0003)					(0.001)	(0.0003)
summer × log(listing)	-0.008^{***}	0.023^{***}					-0.008^{***}	0.023^{***}
	(0.001)	(0.0003)					(0.001)	(0.0003)
weekend			0.021^{***}	0.028^{***}			0.021^{***}	0.028^{***}
			(0.001)	(0.0003)			(0.001)	(0.0003)
weekend × log(listing)			0.001	0.013^{***}			0.001	0.013^{***}
			(0.001)	(0.0002)			(0.001)	(0.0002)
holiday					-0.023^{***}	-0.007^{***}	-0.017^{***}	-0.001^{*}
					(0.001)	(0.001)	(0.001)	(0.001)
holiday × log(listing)					0.001	-0.013^{***}	−0.0005	-0.010^{***}
					(0.001)	(0.0005)	(0.001)	(0.0005)
listing FE	yes	yes	yes	yes	yes	yes	yes	yes
year FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	2,347,006	2,347,006	2,347,006	2,347,006	2,347,006	2,347,006	2,347,006	2,347,006
R^2	0.340	0.940	0.340	0.940	0.339	0.939	0.340	0.941
Note:								*p<0.1; **p<0.05; ***p<0.01

Notes: Estimation results of Equation (23).

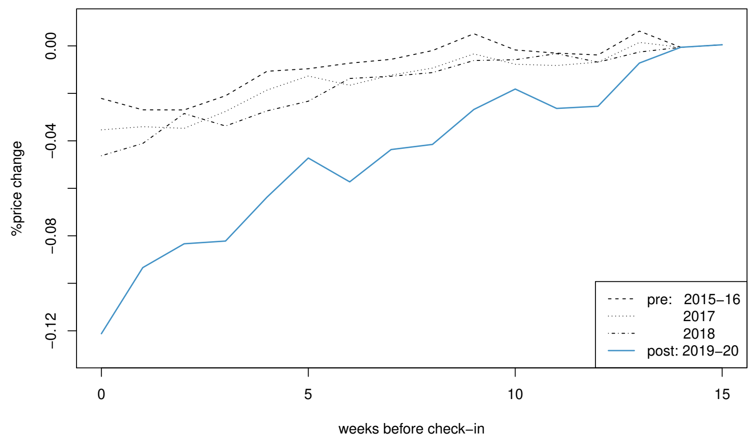
minute discount" feature. In this section, I further investigate sellers' adoption of dynamic pricing after the launch of this feature and the heterogeneity therein.

As an alternative specification, I estimate a regression of log price on a set of lead-time dummies (in weeks) by year, controlling for listing fixed effects δ_j:

$$\log\left(\text{price}_{j\tau t}\right) = \gamma_{\tau-t,y(t)} \cdot \mathbb{I}_{\tau-t} \times \mathbb{I}_{y(t)} + \delta_j + \varepsilon_{j\tau t}, \tag{24}$$

where $\gamma_{\tau-t,y(t)}$ captures the average price path as a function of lead time $\tau - t$ and separately by the year of the sampling date $y(t)$. Figure B.1 shows the change of price profiles by year and demonstrates the 2019 profile trends down more. This change indicates that sellers, on average, tend to adopt dynamic pricing more after the launch of "last-minute discount."

However, a significant lack of dynamic pricing remains after the interface change. If I define



Appendix Figure B.1: Price paths over lead time, by calendar year

Notes: The average seller's dynamic-pricing policy by year. These lines come from regression coefficients from Equation (24). The blue solid line represents 2019 (and early 2020).

dynamic pricing as having a 1% last-month discount or more, 45% of sellers use a dynamic-pricing strategy, compared to 36% before 2019. While this number certainly indicates an increase in dynamic pricing, there are still 55% of sellers—more than half of them—who do not use dynamic pricing after the interface change (see Table B.2). This indicates that changes in the pricing interface is not the only explanation behind the lack of dynamic pricing. I also argue in the paper that optimal dynamic pricing would have implied a price profile that trend down more, suggesting that other explanations might also drive the lack of dynamic pricing.

One further alternative explanation is that some sellers might not know about the new feature. Whereas many sellers have to activate the last-minute discount themselves, the platform explicitly pushed this feature, as part of the "professional hosting tool," to sellers with six or more listings. Appendix Table B.2 shows that six-plus-listing sellers display the same pattern as others: only 46% of them use dynamic pricing after 2019, versus 38% who use dynamic pricing before. The lack of awareness to the feature change is not the first-order explanation.

Appendix Table B.2: Fraction of sellers using dynamic pricing: before and after 2019

	2015-2018	2019-2020
All sample	0.36	0.45
Sellers with six or more listings	0.38	0.46

Notes: Share of listings using dynamic pricing, defined as the average price decline per month of lead time being greater than 1% (in the last four months of lead time).

C Model details

C.1 Demand model detail: aggregation and fixed points

Aggregation. A given day τ of a listing j is listed in market m for at most 12 months (t). In each month in expectation, $\lambda^k_{m\tau t}$ customers of each type $k = 1, 2$ will examine this listing and each customer has $s^k_{j\tau t}$ probability of booking it. Define $S_{j\tau t} = 1$ if *one of* the consumers books listing j, night τ in period t, and $A_{jt\tau} = 1$ if listing j night τ is available at the *beginning* of period t. If consumers choose independently,[35] **?** derives, under a model of homogeneous consumers, the probability that *no customers* from a given segment k book the listing if that night is available:

$$\Pr\left(S_{j\tau t} = 0 | A_{j\tau t} = 1, k\right) = \exp\left(-s^k_{j\tau t} \cdot \lambda^k_{\tau t}\right). \tag{25}$$

Based on this result, the probability that *no customer from either segment* books the listing is

$$\begin{aligned} \Pr\left(S_{j\tau t} = 0 | A_{jt\tau} = 1\right) &= \Pr\left(S_{j\tau t} = 0 | A_{j\tau t} = 1, k = 1\right) \cdot \Pr\left(S_{j\tau t} = 0 | A_{j\tau t} = 1, k = 2\right) \\ &= \exp\left(-s^1_{j\tau t} \cdot \lambda^1_{\tau t} - s^2_{j\tau t} \cdot \lambda^2_{\tau t}\right). \end{aligned} \tag{26}$$

Next, one can write down the expected occupancy rate (i.e., whether night τ of listing j is ever booked) as

$$\begin{aligned} \mathbb{E}\left[\text{occupancy}_{j\tau}\right] = &\Pr\left(S_{j\tau 1} = 1\right) + \Pr\left(S_{j\tau 2} = 1 | A_{j\tau 2} = 1\right) \cdot \Pr\left(A_{j\tau 2} = 1\right) + \\ &\Pr\left(S_{j\tau 3} = 1 | A_{j\tau 3} = 1\right) \cdot \Pr\left(A_{j\tau 3} = 1\right) + \ldots; \end{aligned} \tag{27}$$

that is, the occupancy rate is the sum of the probability that the listing is booked in each period, or the sum of the probability of being available by the start of a period and being booked in the same

[35] I assume away variations in the choice set within the period t.

period.

I now discuss the invertibility of this demand system in order to solve for δ_{jq} given the realized quantity, following Berry et al. (1995) and Berry et al. (2013). Equation (27) outlines the expectation of the occupancy rate conditional on a night being available at the beginning. One can write down the sample analog of this expectation,

$$\frac{1}{|q|}\sum_{\tau\in q}\text{occupancy}_{j\tau}=\frac{1}{|q|}\sum_{\tau\in q}\left(\Pr\left(S_{j\tau 1}=1\right)+\Pr\left(S_{j\tau 2}=1|A_{j\tau 2}=1\right)\cdot A_{j\tau 2}+...\right), \tag{28}$$

which gives the fixed-point equation (10) in section 4.1.

Nested fixed-point algorithm and estimation. I estimate demand using data for each listing j and for each available night τ over all months t of observations during which the listing is available (up to 12 months). The probability of the listing being booked in month τ given availability at the beginning of that month is $\Pr\left(S_{j\tau t}=1|A_{j\tau t}=1\right)$, given by equation (26). The likelihood function is

$$\text{likelihood}=\prod_{j,\tau,t}\Pr\left(S_{j\tau t}=1|A_{j\tau t}=1\right)^{S_{j\tau t}}\cdot\Pr\left(S_{j\tau t}=0|A_{j\tau t}=1\right)^{1-S_{j\tau t}}. \tag{29}$$

To compute the objective function at each set of trial parameters (α,σ,γ), we iterate equation (10) and solve for all δ_{jq}'s as a function of these parameters. I then use the δ's to compute the likelihood. The outer loop then finds the set of parameters that maximizes the log likelihood. The fixed-point computation is costly, but the computation time concentrates on many fixed-point iterations of equations (7)-(10), with mostly the same data (but different parameter values). These computation tasks can be vastly accelerated in a graphical-processing unit (GPU).

C.2 Demand model detail: arrival rates and its identification

Recall that consumers arrive at the Poisson rate given by equation (9). A challenge is to separate $\delta_{jq(\tau)}$ from $\lambda^k_{m\tau t}$, or to separate the customer arrival rate from preferences, given that I only observe the occupancy rate. One needs normalizations. Specifically, I normalize $\gamma^1_{0\bar{m}}=1000$ for zip code 94110 (the largest market in terms of total Airbnb rentals). That is, for segment 1, I assume 1,000 customers will arrive in the *last* month right before the stay date (if the day is not a holiday or weekend, and on January 1 when the week-of-the-year effect is zero), who consider booking listings around the Mission District. For every other zip code, I assume segment 1's last-month arrival rate is proportional to that of 94110's, based on the total number of observed Airbnb rentals. Finally, I assume, for segment 2, $\lambda^2_{t,\tau}=0$ for $\tau\le 4$. That is, no segment 2 customers arrive before eight months to check-in. This normalization should separate the baseline demand intercept from the customer arrival rate.

Whereas this parametrization imposes strong assumptions, in past versions, I have implemented many alternative parameterizations (e.g., assuming different base arrival rates or treating the entire city (rather than zip codes) as a market). The estimated *demand function* is quantitatively stable, perhaps due to the flexible listing-quarter fixed effects.

Further, recall that arrival rates and price coefficients are heterogeneous. Separating the heterogeneous preferences and arrival rates relies on the following arguments. First, the distribution of the timing of when listings are booked identifies γ_1^k given the baseline γ_{0m}^k. Second, the size of segment 2 is identified by changes in the sensitivity to price, weekend, and holiday. If the price sensitivity changes minimally, one rationalizes the data mostly by segment 1. However, if the average price sensitivity changes considerably, one would rationalize the fraction of segment 2 (i.e., $\gamma_{0m}^2/\gamma_{0m}^1$), together with the differences in the price sensitivity (i.e. $\alpha^2 - \alpha^1$), by the empirical pattern of how price sensitivity changes over time.

C.3 Supply: Optimal dynamic pricing with probablistic inaction

Denote the probability of a sale for listing-stay $j\tau$ in period t (i.e., the probability that *one of the customers* book listing j for night τ, during month t) as

$$\begin{aligned} q_{j\tau t} &:= 1 - \Pr\left(S_{j\tau t} = 0 | A_{j\tau t} = 1\right) \\ &= 1 - \exp\left(-s_{j\tau t}^0 \cdot \lambda_{m\tau t}^0 - s_{j\tau t}^1 \cdot \lambda_{m\tau t}^1\right), \end{aligned} \tag{30}$$

and the individual choice probability for each segment $k = 1,2$ is

$$\begin{aligned} s_{j\tau t}^k &= \frac{\exp\left(\delta_{jq} + \alpha^k \log\left((1+r)\cdot p_{j\tau t}\right) + \eta_{j\tau t}\right)}{1 + \exp\left(\delta_{jq} + \alpha^k \log\left((1+r)\cdot p_{j\tau t}\right) + \eta_{j\tau t}\right) + \omega_{jt\tau}^k} \\ &= \left(1 + \frac{1 + \omega_{j\tau t}^k}{\exp\left(\delta_{jq} + \alpha^k \log\left((1+r)\cdot p_{j\tau t}\right) + \eta_{j\tau t}\right)}\right)^{-1}, \end{aligned} \tag{31}$$

where $\omega_{j\tau t}^k = \sum_{j' \neq j} \exp\left(\delta_{j'q} + \alpha^k \log\left((1+r)\cdot p_{j'\tau t}\right) + \eta_{j'\tau t}\right)$ is the sum of exponential utility of other listings, which is a summary statistic of listing j's residual demand. Also, the arrival rate $\lambda_{m\tau t}$ contains time-invariant states about the night, such as whether it is a weekend, holiday, or the effect of seasonality. These states, as well as the lead time τ, are important states that drive the pricing decisions. By comparison, the effect of $\eta_{j\tau t}$ is small, and thus, I set all η to zero when computing optimal prices.

An illustrating example. I start with a two-period problem. In period $T = 12$, pricing is static because the continuation value is zero. Hence, we have

$$\max_p \pi_{j\tau,12}\left(p, \omega_{j\tau,12}\right). \tag{32}$$

The first-order condition is

$$p^*_{j\tau,12} = \frac{c_j}{1-f} - \left(\frac{\partial q_{j\tau,12}}{\partial p_{j\tau,12}}\right)^{-1} q_{j\tau,12}. \tag{33}$$

In period $T - 1 = 11$, the problem is different in two ways. First, if the listing is not occupied in this period, it can still be listed in the next period, creating an option value that drives the prices higher. Second, if the manager gets a chance to act, she knows she might not get another chance to act next period, making her choices today partially tied to her payoff tomorrow. The value function in this period reflects these two elements:

$$\begin{aligned} V_{j\tau,11} = \max_p q_{j\tau,11} \cdot \left(p \cdot (1-f) - c_j\right) + \left(1 - q_{j\tau,11}\right) \cdot \\ \left(\mu_j \mathbb{E}\left[V_{j\tau,12} | \omega_{j\tau,11}\right] + \left(1-\mu_j\right) \mathbb{E}\left[q_{j\tau,12} | \omega_{j\tau,11}\right]\left(p \cdot (1-f) - c_j\right)\right), \end{aligned} \tag{34}$$

where, with 1 minus the probability of a sale, the manager gets her expected payoff renting the listing in month 12 (the option value). However, with probability $1 - \mu_j$, she does not get a chance to change the price and would rent at the same price that she sets now (with μ_j, she enters the optimal decision problem in period 12). Collecting terms and taking the first-order condition, one gets

$$\begin{aligned} &\left(\frac{\partial q_{j\tau,11}}{\partial p} + \frac{\partial\left(\left(1-q_{j\tau,11}\right) \cdot \left(1-\mu_j\right) \mathbb{E}\left[q_{j\tau,12} | \omega_{j\tau,11}\right]\right)}{\partial p}\right)\left(p \cdot (1-f) - c_j\right) + \\ &q_{j\tau,11} \cdot (1-f) + \left(1-q_{j\tau,11}\right)\left(1-\mu_j\right) \mathbb{E}\left[q_{j\tau,12} | \omega_{j\tau,11}\right] \cdot (1-f) + \frac{\partial\left(\left(1-q_{j\tau,11}\right)\mu_j\right)}{\partial p} \mathbb{E}\left[V_{j\tau,12} | \omega_{j\tau,11}\right] = 0, \end{aligned} \tag{35}$$

which is closed form once we solve for $V_{j\tau,12}$.

General problem. In general, one can generally write down the value function as follows, suppressing j and τ subscripts:

$$\begin{aligned} V_t = \max_p (1-f)\left(q_t + (1-\mu)(1-q_t)\mathbb{E}\left[\sum_{\iota=t+1}^{T}(1-\mu)^{\iota-t-1}\left(\prod_{\iota'=t+1}^{\iota-1}(1-q_{\iota'})\right)q_\iota | \omega_t\right]\right)\left(p - \frac{c}{1-f}\right) + \\ (1-q_t)\mathbb{E}\left[\sum_{\iota=t+1}^{T}(1-\mu)^{\iota-t-1}\left(\prod_{\iota'=t+1}^{\iota-1}(1-q_{\iota'})\right)\mu V_\iota | \omega_\tau\right]. \end{aligned} \tag{36}$$

This value function can be solved in closed form via backward induction. Denote

$$\Delta_t = (1-f)\left(q_t + (1-\mu)(1-q_t)\mathbb{E}\left[\sum_{\iota=t+1}^{T}(1-\mu)^{\iota-t-1}\left(\prod_{\iota'=t+1}^{\iota-1}(1-q_{\iota'})\right)q_\iota|\omega_t\right]\right) \tag{37}$$

and

$$\Omega_t = (1-q_t)\mathbb{E}\left[\sum_{\iota=t+1}^{T}(1-\mu)^{\iota-t-1}\left(\prod_{\iota'=t+1}^{\iota-1}(1-q_{\iota'})\right)\mu V_\iota|\omega_t\right], \tag{38}$$

and one can write the FOC in a simple term:

$$p_t^* = \frac{c}{1-f} - \left(\frac{\partial \Delta_t}{\partial p}\right)^{-1}\left(\Delta_t + \frac{\partial \Omega_t}{\partial p}\right). \tag{39}$$

Counterfactual: pricing with platform-assisted adjustments. What happens when the platform first proposes a price-adjustment function, and sellers set one price for each listing given this function? This section outlines the seller optimal pricing under this counterfactual scenario.

Denote seller price as $\bar{p}_{jq}$ and platform's adjustment factor as $a_{ml\tau t}$ (for market m, listing-type l, night τ, and based on time before checkin $t-\tau$). The final price before tax and consumer fee is $(1+a_{ml\tau t})\bar{p}_{jq}$. We can write the seller objective as (suppress m and l)

$$\begin{aligned}
&\max_p \sum_\tau \Bigg(q_{j\tau,1}\left((1-f)\left(1+a_{ml\tau,1}\right)p - c_j\right) + \left(1-q_{j\tau,1}\right)q_{j\tau,2}\left((1-f)\left(1+a_{ml\tau,2}\right)p - c_j\right) + \\
&\left(1-q_{j\tau,1}\right)\left(1-q_{j\tau,2}\right)q_{j\tau,3}\left((1-f)\left(1+a_{ml\tau,3}\right)p - c_j\right) + \ldots + \prod_{\iota=1,\ldots,11}\left(1-q_{j\tau,\iota}\right)q_{j\tau,12}\left((1-f)\left(1+a_{ml\tau,12}\right)p - c_j\right)\Bigg) \\
=&\max_p \sum_\tau \left(\sum_{t=1}^{T}\prod_{\iota\le t-1}\left(1-q_{j\tau,\iota}\right)q_{j\tau,t}\left((1-f)\left(1+a_{ml\tau,t}\right)p - c_j\right)\right).
\end{aligned}$$

Taking the first-order condition,we arrive at the "base price" of each listing at

$$p_j^{\text{counterfactual}} = -\frac{\Sigma_\tau\Sigma_t\left((1-f)\left(1+a_{ml\tau,t}\right)\prod_{\iota\le t-1}\left(1-q_{j\tau,\iota}\right)q_{j\tau,t} - \left(\frac{\partial q_{j\tau,t}}{\partial p}\prod_{\iota\le t-1}\left(1-q_{j\tau,\iota}\right) - \Sigma_{\iota'\le t-1}\frac{\partial q_{j\tau,\iota'}}{\partial p}\prod_{\iota\ne\iota'}\left(1-q_{j\tau,\iota}\right)q_{j\tau,t}\right)\times c_j\right)}{\Sigma_\tau\Sigma_t\left(\frac{\partial q_{j\tau,t}}{\partial p}\prod_{\iota\le t-1}\left(1-q_{j\tau,\iota}\right) - \Sigma_{\iota'\le t-1}\frac{\partial q_{j\tau,\iota'}}{\partial p}\prod_{\iota\ne\iota'}\left(1-q_{j\tau,\iota}\right)q_{j\tau,t}\right)(1-f)\left(1+a_{ml\tau,t}\right)}.$$

D Uniform-pricing instruments: details

To identify the price coefficient, I leverage the pricing frictions to construct a price shifter based on prices of other, unrelated nights. Nights that are far from the focal date have plausibly uncorrelated demand shocks (given listing-quarter fixed effects) but are often set at the same price. This section demonstrates the strength of the instrument and performs several robustness checks.

I estimate

$$\log\left(\text{price}_{j\tau t}\right) = \beta^1 \log\left(\bar{\text{price}}_{j,-q,t-1}\right) + \delta^1_{jq} + X_\tau\gamma^1 + u_{j\tau t}, \tag{40}$$

where X_τ are weekend, month-of-the-quarter, and holiday indicators, and δ^1_{jq} are listing-quarter fixed effects. I use this same set of controls in structural demand estimation. The excluded variable ("instrument") is the log price of nights in other quarters observed in the previous month, $\log\left(\bar{\text{price}}_{j,-q,t-1}\right)$. Given the first stage, I estimate the second stage of the IV regression,

$$\text{sale}_{j\tau t} = \alpha^2 \log\left(\hat{\text{price}}_{j\tau t}\right) + \delta^2_{jq} + X_\tau \gamma^2 + \varepsilon_{j\tau t}, \tag{41}$$

where $\text{sale}_{j\tau t}$ is an indicator of whether one customer occupies night τ in month t.

I find that, given the set of controls, the log price of other nights is still strongly correlated with the focal date's price. The F-statistic of the excluded variable is on the order of 10,000. I find the second-stage linear-log price coefficient is -0.467, implying an average price elasticity of -2.4, which is close to the structural estimate. This exercise confirms the source of identification in the structural model and that the driver of price variation is strong.

I further perform two robustness checks and one placebo test. First, one might be concerned that the IV recovers the *local* average price coefficient for uniform-pricing listings, which might systematically differ from others. To address this concern, I estimate the same first- and second-stage regressions using a sub-sample of listings with high degrees of price variation. I take the top quartile of listings with the highest price variation. Column 2 shows this subset gives virtually the same price coefficient from the IV estimate, implying price-elasticity heterogeneity across listings is not correlated with the listings' degree of price variation.

Second, one might be concerned some correlations remain in demand shocks between the nights that are used to construct the IV and the focal night. I perform a robustness check including nearby nights to construct the IV, and show the results are robust to excluding these nearby nights. Column 3 of the table shows the second-stage result is virtually unchanged. This finding suggests demand shocks are not systematically correlated across nearby nights, and one should not worry about exactly what cutoff to take when constructing the IV.

Finally, one might wonder how the uniform-pricing IV compares with using lagged prices as IVs. In this case, a concern about using the lagged price as the IV is the presence of night(τ)-specific demand shocks. Column 4 shows the result of using the lagged price of the focal night as the IV for the current price. The second-stage estimate is only one third of the preferred specification, implying a price elasticity of about -0.8, and is very different from the uniform-pricing IV estimate.

E Additional tables

Appendix Table D.1: Uniform-pricing instruments and alternative specifications

Panel A: first stage

	Dependent variable: log(price)			
	(1)	(2)	(3)	(4)
log(avg lag price, diff quarter)	0.150***	0.114***		
	(0.001)	(0.003)		
log(avg lag price, all dates)			0.222***	
			(0.001)	
log(lag price, same date)				0.560***
				(0.0005)
weekend	0.028***	0.100***	0.028***	0.013***
	(0.0001)	(0.001)	(0.0001)	(0.0001)
holiday	−0.0004	−0.007***	−0.0005	−0.0004
	(0.0003)	(0.001)	(0.0003)	(0.0003)
days to checkin	0.001***	0.002***	0.001***	0.001***
	(0.00001)	(0.00004)	(0.00001)	(0.00001)
days to checkin squared	−0.00001***	−0.00001***	−0.00001***	−0.00001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
listing × checkin quarter FE	yes	yes	yes	yes
week, weekend, holiday FE	yes	yes	yes	yes
Observations	3,601,194	498,281	3,601,194	3,471,476
R^2	0.970	0.909	0.970	0.979

Note: *p<0.1; **p<0.05; ***p<0.01

Panel B: second stage

	Dependent variable: occupancy			
	(1)	(2)	(3)	(4)
log(price)	−0.467***	−0.510***	−0.447***	−0.137***
	(0.017)	(0.048)	(0.012)	(0.003)
weekend	0.022***	0.061***	0.021***	0.013***
	(0.001)	(0.005)	(0.001)	(0.0004)
holiday	−0.005***	−0.012***	−0.005***	−0.005***
	(0.001)	(0.003)	(0.001)	(0.001)
days to checkin	−0.010***	−0.010***	−0.010***	−0.010***
	(0.00004)	(0.0001)	(0.00003)	(0.00003)
days to checkin squared	0.00005***	0.0001***	0.00005***	0.00005***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
listing × checkin quarter FE	yes	yes	yes	yes
week, weekend, holiday FE	yes	yes	yes	yes
Observations	3,601,194	498,281	3,601,194	3,471,476
R^2	0.275	0.223	0.276	0.289

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: first and second stage of IV estimates of sales (probability that one consumer rents the listing in a given month) on price, where the price is instrumented by the average lagged price of nights that are in different quarters of the focal date ("uniform-pricing IV"). Alternative IVs are compared.

Appendix Table E.1: Fixed costs: auxiliary parameter estimates

	par est	std err
post 2018 regulation	-0.714	0.077
distance to union sq	-2.585	0.174
distance squared	0.615	0.047
scale of the fixed cost error	3.090	0.103

Notes: Reports fixed-cost parameters except for segment-specific average fixed cost (summarized in Figure 8).

Appendix Table E.2: Decomposition of supply-side primitives on listing and seller characteristics

	c_j (\$)	se	θ_j (%)	se	μ_j (%)	se	ρ_j (nr)	se
intercept	-4.4	8.1	49.0	5.8	74.9	6.3	5.8	1.7
log(nr listing)	6.0	0.4	5.9	0.3	-6.8	0.3	2.7	0.1
host is superhost	-0.6	0.6	-0.1	0.4	-2.2	0.5	-0.3	0.1
respond in 1 day	-9.3	0.7	0.9	0.5	0.7	0.6	0.0	0.1
instant booking	-6.0	0.6	-0.1	0.4	-2.1	0.5	0.2	0.1
flexible cancellation	7.6	0.7	-0.1	0.5	-1.9	0.5	-1.0	0.1

Notes: Regression results of estimated supply parameters on observed listing and seller characteristics. Additional controls not reported in the table are fully saturated listing type (e.g. entire apartment) × max number of guests × property type (e.g., townhouse) fixed effects, amenity indicators (TV, internet, parking, washer/dryer, breakfast, allow pets), and length of the listing's descriptions.

Appendix Table E.3: Supply-side estimates: top 75 segments

	% of sample	marginal cost (\$)	std err	prob(adjust price) (μ, %)	std err	expected nr. unique prices (ρ)	std err	dynamic pricing (θ, %)	std err	fixed costs (\$)	std err
group001	2.6	9.5	0.0	100.0	81.5	0.6	0.2	9.1	0.0	6043.5	314.7
group002	2.3	16.4	0.4	100.0	3.8			100.0	1.0	6358.1	307.6
group003	2.2	14.3	0.3	21.4	1.2			100.0	0.4	6271.1	316.2
group004	2.2	16.4	0.4	0.0	0.0	0.2	0.1	6.5	3.2	5175.8	280.6
group005	2.0	24.9	0.4			2.6	0.3	0.2	5.2	4433.9	276.0
group006	1.9	-21.9	0.5	38.9	3.2	0.0	0.2	71.4	2.3	5990.7	286.5
group007	1.9	12.8	0.4	100.0	3.5	0.0	0.4	84.8	1.9	4800.8	260.5
group008	1.9	21.9	0.3	100.0	40.0	0.5	0.3	16.4	3.1	3769.8	264.9
group009	1.9	19.0	1.8	0.0	9.3	0.1	0.5	9.3	14.7	4785.9	308.0
group010	1.7	41.3	0.4			0.1	0.0	0.0	0.0	7316.3	384.9
group011	1.6	90.1	0.4	0.0	0.3	0.0	0.0	76.2	0.5	6306.1	345.7
group012	1.5	68.4	1.6			0.2	0.2	0.0	1.9	6532.7	358.9
group013	1.5	40.9	0.4	100.0	8.7	0.0	0.1	37.1	1.8	4077.1	289.8
group014	1.4	23.1	0.4	100.0	0.8	0.0	1.3	97.4	0.9	3991.7	273.9
group015	1.4	35.8	0.4	100.0	7.0	0.1	0.3	39.4	6.1	3534.2	282.1
group016	1.3	35.5	0.4	10.0	2.1	0.1	1.2	74.6	3.6	4150.2	302.4
group017	1.3	26.6	0.4			3.1	0.5	0.0	0.0	4333.0	319.7
group018	1.2	25.5	0.6	100.0	51.4	13.6	2.8	9.0	0.1	4660.3	331.1
group019	1.2	97.8	0.7	0.0	0.1			100.0	11.3	5075.8	327.0
group020	1.2	49.4	0.4	100.0	53.0	17.3	8.2	5.6	5.5	4755.2	335.2
group021	1.1	32.2	0.3	100.0	7.1			100.0	2.9	5413.9	399.3
group022	1.1	1.0	1.5	8.4	9.3	0.2	0.7	38.0	6.4	5496.1	390.4
group023	1.0	11.6	0.4	100.0	14.5	0.0	0.5	57.1	4.6	3925.4	286.5
group024	1.0	0.1	2.0	100.0	163.3	2.1	0.1	5.9	0.2	7642.2	492.5
group025	0.9	14.5	0.3	100.0	10.0	0.0	0.3	60.0	2.7	3883.8	330.4
group026	0.9	192.4	0.3	78.3	4.4			100.0	2.6	5099.9	380.8
group027	0.9	28.1	0.4	0.1	4.6	0.0	0.2	22.6	3.6	6980.1	441.0
group028	0.9	51.4	0.4	100.0	3.3	31.0	2.7	41.6	2.2	2274.7	328.3
group029	0.9	15.8	0.5	100.0	194.9	2.5	0.5	4.0	6.7	3503.1	349.2
group030	0.9	31.4	0.4	95.6	19.5	31.0	3.9	19.3	4.0	3874.7	356.9
group031	0.9	531.5	0.7	38.9	9.8	31.0	8.0	33.3	10.7	3709.2	515.4
group032	0.9	64.6	0.4	100.0	79.5	12.3	1.2	2.4	1.9	5619.4	386.2
group033	0.9	34.7	0.3	0.0	0.0	3.9	0.7	6.1	1.7	4961.1	439.8
group034	0.9	35.3	0.4	99.9	746.0	0.0	0.4	0.9	7.6	5624.8	447.6
group035	0.9	20.0	0.3	100.0	3.9	0.3	3.9	90.8	2.5	2771.8	332.5
group036	0.9	120.9	0.3	100.0	2.1			100.0	2.3	5117.9	427.5
group037	0.8	-12.0	0.5	0.0	3.6	0.0	0.4	19.9	3.7	5856.9	437.5
group038	0.8	71.5	0.6	0.0	2.2	12.6	103.2	99.0	2.6	6339.8	405.8
group039	0.8	30.4	0.8	0.0	10.4	0.2	0.8	40.3	8.2	4311.9	405.2
group040	0.8	22.9	0.0	100.0	2598.2	0.2	1.1	0.5	36.8	5224.5	454.3
group041	0.8	19.8	0.4	100.0	4.3	15.3	87.1	97.9	2.9	2814.7	352.5
group042	0.8	88.8	0.5	0.0	0.0	31.0	5.5	62.6	1.2	6179.5	417.2
group043	0.8	12.8	0.4	100.0	8.7	2.9	1.3	49.0	7.8	2341.3	361.2
group044	0.8	80.9	0.4			0.2	0.1	0.0	2.8	4530.9	401.4
group045	0.8	49.4	0.5	100.0	6.8	0.0	1.3	76.1	8.1	5897.0	474.3
group046	0.8	26.5	0.4	99.8	1.5	0.1	1.2	92.2	1.4	2224.1	353.3
group047	0.8	30.0	0.5			31.0	7.6	0.0	0.0	4798.0	409.7
group048	0.8	128.3	0.4	99.2	6.6	1.1	0.2	42.8	2.8	4522.8	409.1
group049	0.8	33.8	0.5	99.9	16.7	30.7	3.4	10.6	2.8	3681.3	380.9

Appendix Table E.4: Supply-side estimates: bottom 75 segments

	% of sample	marginal cost ($)	std err	prob(adjust price) (μ, %)	std err	expected nr. unique prices (ρ)	std err	dynamic pricing (θ, %)	std err	fixed costs ($)	std err
group076	0.5	19.9	0.4	30.3	3.0	3.3	0.9	42.8	1.6	1964.4	458.8
group077	0.5	91.2	0.0	0.0	0.0			100.0	0.0	6034.0	547.4
group078	0.5	24.0	0.5	100.0	77.8	4.8	0.5	8.3	3.7	3205.6	436.3
group079	0.5	32.4	0.4	61.6	6.1			100.0	7.1	2108.0	436.7
group080	0.5	85.6	0.3	100.0	2.2			100.0	0.8	5267.6	539.9
group081	0.5	9.4	0.5	100.0	11.2	1.5	0.2	34.8	3.2	1903.4	460.4
group082	0.5	232.0	0.6	100.0	42.3	0.9	0.5	17.3	7.7	6764.2	640.8
group083	0.5	47.9	0.3			15.0	17.6	0.0	0.0	11971.8	1181.4
group084	0.5	254.9	0.3	10.8	2.5			100.0	2.4	5629.1	548.4
group085	0.5	226.6	0.3	100.0	0.9			100.0	0.7	4564.6	486.5
group086	0.5	102.6	0.6	10.8	9.4			100.0	2.7	14165.0	2251.5
group087	0.5	27.9	0.4	19.0	1.8	0.0	1.3	90.3	1.4	2476.2	440.5
group088	0.5	34.7	0.4	73.5	1.9			100.0	3.0	2238.0	463.0
group089	0.5	26.9	0.4	50.8	6.8	5.6	0.6	55.7	2.8	4310.2	498.2
group090	0.5	64.4	0.4	7.4	3.1	31.0	35.9	88.9	2.6	3919.2	511.2
group091	0.5	20.6	0.4	92.9	62.3	6.3	1.1	10.5	3.8	3436.2	449.1
group092	0.5	11.9	0.4	34.3	1.8			100.0	0.5	2001.0	445.3
group093	0.5	136.8	0.4			8.6	0.9	0.0	32.6	5416.8	526.4
group094	0.5	36.9	0.7	1.3	3.8			100.0	13.6	3308.1	427.0
group095	0.4	177.1	1.1	0.2	3.4			100.0	4.4	11813.7	1616.3
group096	0.4	19.2	0.4	13.8	3.8	5.1	5.6	68.5	9.7	4114.2	475.6
group097	0.4	78.3	0.4	100.0	1.7	0.0	44.4	99.4	2.6	6101.6	593.1
group098	0.4	101.6	0.8	0.0	1.2			100.0	1.6	3493.3	481.5
group099	0.4	-15.6	0.8	9.1	4.0	0.0	0.1	33.1	2.9	4322.9	516.7
group100	0.4	12.7	0.4	100.0	9.0	0.0	0.3	66.6	2.7	3925.4	286.5
group101	0.4	12.6	0.4	100.0	80.4	14.5	6.7	17.0	11.4	4257.3	520.0
group102	0.4	99.9	0.6	32.7	2.2			100.0	4.0	6343.7	733.0
group103	0.4	14.4	0.5	100.0	0.2	31.0	271.6	99.4	1.3	2146.0	478.0
group104	0.4	25.0	0.4	100.0	80.4	3.7	0.8	8.0	0.1	6719.6	688.3
group105	0.4	67.9	0.4	100.0	0.2			100.0	0.1	8603.4	872.4
group106	0.4	-16.4	0.4	0.0	1.9	0.3	0.1	39.6	1.9	7025.2	594.8
group107	0.3	149.3	0.9	0.0	6.6	0.1	2.9	79.6	6.9	2393.2	480.4
group108	0.3	72.1	0.3	100.0	1.6			100.0	0.6	2790.3	522.5
group109	0.3	25.9	0.4	100.0	2.2	0.0	1.9	78.2	1.1	264.2	632.0
group110	0.3	94.3	0.4	0.0	0.7			100.0	2.0	2853.8	551.2
group111	0.3	65.4	0.4	51.5	2.4			100.0	5.7	2534.6	502.3
group112	0.3	52.8	0.4	78.9	36.5	31.0	6.4	17.2	6.1	3372.8	510.8
group113	0.3	25.0	0.4	0.0	2.6			100.0	0.2	4775.7	640.1
group114	0.3	169.6	0.4	100.0	1.3	16.2	0.9	42.5	0.9	6592.1	751.2
group115	0.3	39.2	0.4	24.4	1.3	0.0	1.5	86.7	2.6	2054.9	553.7
group116	0.3	32.2	0.5	43.8	14.4			99.9	15.0	4049.0	608.1
group117	0.3	95.1	0.4			5.7	0.7	0.0	2.7	4035.3	553.9
group118	0.3	17.2	0.5	100.0	8.8	24.1	14.4	67.3	4.7	3764.1	609.2
group119	0.3	26.7	0.5	100.0	234.7	0.3	0.6	3.7	14.8	13191.7	1854.4
group120	0.3	28.8	0.4	79.3	9.1	28.0	72.2	84.4	8.6	6123.4	736.9
group121	0.3	100.2	0.6	12.3	2.2			100.0	1.5	7983.6	809.5
group122	0.3	9.4	0.4	75.9	4.6	1.4	0.3	59.4	1.7	4741.6	527.9
group123	0.3	98.3	0.5	90.8	0.5	31.0	28.9	97.1	1.4	4037.2	566.8
group124	0.3	57.6	0.7	0.0	6.0			100.0	5.6	-393.4	557.8
group125	0.3	91.8	0.3	100.0	2.7			100.0	0.6	10326.0	1469.7
group126	0.3	-24.7	0.4	2.2	0.6			100.0	0.3	9931.5	766.8
group127	0.3	19.4	0.3	100.0	2.9			100.0	1.1	3206.0	578.5
group128	0.3	182.9	0.4	0.0	1.4			100.0	2.4	12865.9	1481.3
group129	0.2	15.4	0.0	53.9	0.0	4.5	Inf	53.9	Inf	10409.1	900.2
group130	0.2	89.5	0.3	0.1	0.8			100.0	1.2	14664.8	2259.5
group131	0.2	24.9	0.6	90.4	2016.2	25.8	3.5	0.4	1.7	7149.5	903.4
group132	0.2	15.4	0.0	53.9	0.0	4.5	Inf	53.9	Inf	58238.9	52386.7
group133	0.2	95.2	0.4	99.0	0.5			100.0	1.1	4201.5	662.7
group134	0.2	101.2	0.3	20.6	1.5			100.0	1.9	5115.1	826.8
group135	0.2	48.1	0.3	99.9	1.9	8.9	0.7	65.5	0.9	6916.0	746.5
group136	0.2	73.5	0.5	48.4	2.5			100.0	2.3	6162.9	1000.7
group137	0.2	72.8	0.3	100.0	3.4			100.0	2.5	48969.9	52381.5
group138	0.2	38.1	0.4	72.0	1.6	31.0	23.8	94.9	1.1	2686.9	873.9
group139	0.2	-8.3	0.6	67.5	52.2	1.2	0.2	9.6	3.8	1958.5	890.9
group140	0.2	2.2	0.4	96.2	0.5	23.0	39.6	97.4	0.3	5764.3	828.9
group141	0.2	25.9	0.6	100.0	2.8	0.5	75.7	99.7	2.8	3289.5	849.7
group142	0.1	431.7	0.5	90.5	0.9	30.7	23.1	92.6	0.6	6067.1	1253.4
group143	0.1	44.8	0.4	99.9	0.2			100.0	1.4	3695.6	912.9
group144	0.1	99.3	0.4	98.3	0.3			100.0	0.9	4795.0	929.9
group145	0.1	24.0	0.4	77.6	3.3			100.0	3.2	3925.4	286.5
group146	0.1	108.1	0.5	90.6	1.7	31.0	11.1	84.0	2.6	3925.4	286.5
group147	0.1	108.1	0.4	99.8	0.1			100.0	1.2	3925.4	286.5
group148	0.0	901.4	0.0	50.4	0.0	18.4	Inf	51.8	0.0	3925.4	286.5
group149	0.0	140.1	0.4	100.0	0.1	14.5	112.4	99.2	0.2	3925.4	286.5
group150	0.0	-50.0	150.2	100.0	240.2	0.0	0.5	63.5	5.2	3925.4	286.5

Notes: Supply-side estimates for the bottom 75 segments.