Information, Managerial Incentives, and Scale: Evidence from Hotel Pricing

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Abstract

I study why some firms have better information about market demand than their rivals, with application to the hotel industry. Hotel chains delegate pricing to their franchisees and extract royalty payments as a percentage of revenues; larger chains charge higher royalties. Franchisees affiliated with larger hotel chains may have better information about demand because larger chains have more data, or they may have worse information because higher royalties weaken franchisee incentives to gather information. I develop a novel method to infer the quality of firms' information from price and quantity data by using common-knowledge demand shocks. I use this method to show that hotels affiliated with large chains have worse information than hotels affiliated with smaller chains. In a counterfactual setting in which royalties are fixed across chains, large chains become better-informed than small chains, suggesting that franchisee effort in gathering information is an important driver of information quality.

JEL Codes: L11, L22, L25, L83, M52

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1 Introduction

In markets where demand is difficult to predict, the ability to forecast demand before choosing prices can be a key determinant of firm performance. However, we know relatively little about which characteristics of the firm determine how well-informed that firm is about demand when it sets prices. One common argument is that firms obtain better information through scale. Larger firms may have better information about the market because they have access to bigger data sets and more sophisticated analytical tools. If this is the case, the largest firms in an industry may become even more dominant over time, generating a "winner take all" outcome. Another theory posits that information quality is driven by the incentives for managers to gather information. If these incentives are stronger at smaller firms, larger firms may in fact be at an informational disadvantage. In this case, firms may even take actions that reduce market concentration. For instance, upstream firms may vertically disintegrate if doing so provides downstream managers with stronger incentives to gather information. In this sense, information and competition could even be complementary, as in Bloom *et al.* (2016).

While the scale argument has been used extensively to explain recent growth in market concentration—particularly in the digital economy (Scott Morton *et al.* , 2019)—there have not been similar increases in concentration in other industries where informational advantages are crucial. Ultimately, in order to gauge whether a market may experience consolidation due to informational advantages, it is important to understand the role of both scale and incentives in determining firms' information quality.

The hotel industry has several features that make information about the market—particularly information about demand and rivals' prices—especially valuable to firms when setting prices. Demand can be difficult to predict, and capacity constraints exacerbate the costs of mispricing (see, e.g., Williams (2018) on airlines). A hotel might sell out of rooms early in the booking window if it sets a price that is too low. However, the hotel industry has not consolidated in the way that other information-intensive markets have consolidated. In fact, there has been a wave of vertical *dis*integration in the hotel industry over the past twenty years (Roper, 2017). Hotel chains have moved from dual distribution models, in which some properties are owned and operated by the chain while others are franchised, to pure franchising models. Furthermore, hotel chains delegate the daily operations of each property, including setting prices, to the franchisee. These franchisees and the management companies they hire typically are considerably smaller than the upstream chain.

In this paper, I investigate how information quality varies across hotels. I pay particular attention to the question of managerial incentives (as determined by the vertical contract between chain and franchisee) versus scale (as determined by the size of the chain). The scale argument posits that franchisees affiliated with bigger chains have better information than small-chain and independent rivals. At the same time, franchisees affiliated with smaller chains have stronger incentives to gather information, because they pay smaller royalties to the upstream franchisor and thus receive to a larger share of the hotel's revenues.

I first present evidence that suggests that hotels are poorly informed about certain aspects of market demand. Using a year of data on nightly hotel prices and occupancies for several U.S. college towns, I show that hotel prices systematically respond more to predictable shifts in market-level demand than to unpredictable shifts in market-level demand. Predictable positive shifts in demand, such as those arising from graduation and home football games for the college, are associated with significant increases in price and occupancy. Comparable positive shifts in demand not associated with such predictable events, on the other hand, are associated with much smaller increases in price, even though we have little reason to believe hotels should respond to these shocks differently if they were fully informed about them. This suggests that hotels are not as well-informed about these shifts when choosing prices.

Although this evidence suggests that there is imperfect information about some demand variation, I require a formal framework to more credibly measure information quality. I introduce a novel methodology to infer firms' information about market-wide demand shifts from market data (i.e., prices and quantities). I model information as a private signal of a market-wide demand shifter, where a market is a city on a given night. Hotels set prices according to their expectations over rivals' prices, and these expectations are influenced by the signal. My model accounts for the fact that hotel pricing is a complicated, dynamic process that cannot be summarized by nightly data alone. Much attention has been drawn to this problem, particularly in the revenue management and operations literature (see Cho *et al.* (2018) and Zhang & Weatherford (2016)). In order to manage this complication, I specify hotel-specific price policy functions that are based on detailed hotel revenue management models (Cho *et al.* , 2018) and sufficiently flexible to explain pricing patterns in the data.

I show that the signal structure is nonparametrically identified, jointly with hotels' pricing policy functions, from price and quantity data for a series of markets with the same firms (e.g., the same city over many nights). Having identified demand for hotels on each night, I can partition market-wide demand shifters into features of the market that I assume are common knowledge (e.g., day of week or a home football game in a large college town) and all residual market-level variation in demand, which I do not assume is common knowledge.

Loosely speaking, I establish identification by comparing how hotels respond to the common knowledge demand shifter versus how they respond to the residual variation. If a hotel is much more responsive to the known shifter than to the residual, I infer that the hotel has poor information about the residual. This parallels the strategy used in my descriptive analysis, with the residual variation as the source of "unpredictable" demand variation and the common-knowledge demand shifters as the source of "predictable" demand variation.

I then estimate a parameterized version of this model using data from eighteen U.S. college towns. I measure information quality as a signal-to-noise ratio. I find that this ratio is 3.68 times larger for the 75th percentile firm than for the 25th percentile. That is, by this measure, the 75th percentile firm has over three times better information than the 25th percentile firm. If a hotel manages to obtain perfect information (holding all rivals' information constant), I estimate it would increase its annual revenue by 3.50% on average. Hotels with poor information quality have the most to gain: conditional on being below the median information quality, I estimate hotels would increase annual revenues by 4.71% on average by unilaterally obtaining perfect information.

I then examine which characteristics of the firm best predict information quality. I partition hotels into three groups: those affiliated with large "upscale" chains, those affiliated with large "downscale" chains, and hotels that are either independent or affiliated with small chains. The large upscale chains are those that operate full-service flagship properties as a significant source of revenue and are generally considered industry leaders in terms of resources, profitability, and sophistication. I find that, conditional on the geographic market, hotels affiliated with the industry leaders have worse information quality. The point estimate of the difference in information quality between upscale large chain and small chain or independent hotels is quite large: I estimate the difference between upscale large and small chains is, on average, roughly the same as the difference between the median and 70th percentile hotel in my entire sample, according to information quality.

Next, I show that the gap between upscale large chains' information and small chains' information can be explained by differences in franchisee effort. I estimate that higher royalty fees predict worse information quality. This is consistent with a standard moral hazard argument: the higher the royalty fees, the smaller the percentage of revenues the franchisee pockets. This implies that the marginal benefits of collecting information become smaller relative to the marginal costs of the franchisee's information-gathering effort, which do not vary with the royalty. As a result, higher royalty fees induce less information-gathering effort by franchisees.

I conduct a counterfactual analysis in which all hotels pay the median royalty fee of 11%. I use my supply and demand estimates to predict marginal increases in expected annual revenues from obtaining better information, and use these estimates to estimate the cost of information-gathering effort. This allows me to predict counterfactual information quality under any royalty structure. In the counterfactual in which all royalties are 11%, I predict large upscale hotel chains have better information than small chains. My point estimate of this counterfactual difference is roughly the same size (but with opposite sign) as the estimated actual difference between small chains' and large upscale chains' information. This suggests that the effect of differences in royalty rates is approximately twice as large as the cumulative effect of all other factors that determine differences information quality.

My interpretation of these results is that, in the hotel industry, managerial information-gathering incentives are a key determinant of information quality. I interpret this as evidence that local information is particularly important to hotels. Because franchisees are the "boots on the ground," they may be better-positioned than the upstream chain to gather local information about demand in their market. This explains the features of the hotel industry I initially highlighted: vertical disintegration and pricing delegation. Chains delegate pricing to franchisees because the franchisee is best-positioned to gather the most important information, and they vertically disintegrate in order to provide the franchisee stronger incentives to gather information. Furthermore, because I do not find evidence that scale itself significantly improves information quality, consolidation (e.g., upstream mergers between chains) should not substantially affect the quality of information hotels have about the market. This is in contrast to other industries in which information is more "global" than "local," where we may be more concerned about informational advantages of scale causing rapid consolidation.

The remainder of this paper is organized as follows: I first outline the literature related to this paper. In section 2, I describe the hotel industry and my data and provide preliminary evidence that hotels do not have perfect information about demand when pricing. In section 3, I outline the general model and discuss identification of information quality. In section 4, I discuss my empirical specification and estimation. I report estimates, document patterns in information quality, and conduct counterfactuals in section 5. Section 6 concludes.

Related Literature

In documenting heterogeneity in firms' information quality and measuring its consequences for firm performance, this paper broadly relates to an extensive literature on productivity differences across firms. Syverson (2011) provides a complete summary up to that point. This summary outlines several main explanations for productivity differences; my paper relates to three in particular. The first is differences in managerial practices (Bloom & Van Reenen (2007), Bloom *et al.* (2016)). The second is differences in information technology (IT) adoption (Hubbard (2003), Bloom *et al.* (2012)). The third is differences in organizational form, measured either as degree of vertical integration or firm size (Shepard (1993), Atalay *et al.* (2014)). These papers quantify the effects of each of these causes on firm productivity in turn.[1] None of these papers examine more than one of these contributors to productivity in one framework. Relative to this literature, my paper makes a trade-off: I study information about demand as a specific mechanism through which productivity gains are generated, which allows me to examine several potential drivers of firm productivity, such as managerial incentives, the practices these incentives induce, and scale, in one cohesive framework.[2]

There are relatively few empirical papers that study how information-gathering incentives affect the relationship between upstream and downstream parties.[3] Lo *et al.* (2016) examine how the competitive environment affects the degree to which firms delegate pricing to a sales force. They build a model that captures agents' incentives to gather information. A key determinant of the integration decision in Forbes & Lederman (2009) and the delegation decision in Dessein *et al.* (2019) and Dessein & Santos (2016) is the importance of adaptability to local conditions relative to the ability to coordinate. While my paper does not explicitly model the delegation decision and thus does not contribute to this literature directly, it supports many of its theoretical conclusions (Aghion & Tirole (1997), Dessein & Santos (2006), Alonso *et al.* (2008)). Hotels vertically disintegrate because local knowledge is important is consistent with this literature. My paper is complementary to the empirical papers in this literature because it explicitly measures information instead of using a proxy for its importance. Furthermore,

[1]It should be noted that the third cause —- organizational form—is difficult to disentangle from management practices. For instance, Atalay *et al.* (2014) conclude that larger firms are more productive because they spread "intangible inputs"—which could include good management practices—to a larger number of plants.

[2]A few papers in the productivity literature have married some of these strands. For instance, the literature on CEO compensation (Bertrand & Mullainathan, 2003) examines how incentives induce best management practices, albeit for a very specific kind of manager. Bajari *et al.* (2019) study whether amount of data improves the ability to forecast demand using data from Amazon. My paper differs in that I study a novel channel through which the firm's organization affects market outcomes and firm performance—quality of information about market demand—and model this channel in a way that allows me to examine market outcomes like prices and quantities in a number of counterfactual settings.

[3]There is a much broader empirical literature on vertical integration (Crawford *et al.* (2018), Murry (2017), and others; Lafontaine & Slade (2007) summarize the literature until that point) that has examined mechanisms through which arrangements between upstream firms (e.g., chains) and downstream firms (e.g., franchisees) affect market outcomes. None of these papers examine the consequences of vertical contracts on information.

my paper expands on this literature by drawing implications for firm productivity.

Methodologically, because this paper measures information quality about a common demand shifter, the closest analogues are found in the common values auctions literature. Common values auctions are notoriously difficult to identify; papers have either emphasized negative (non-identification) results (as in Athey & Haile (2002)), relied on functional form assumptions (Bajari & Hortaçsu, 2003), or focused on tests for common values rather than identification of the full model (Haile *et al.* , 2003).[4] My approach bears some similarity to Hendricks & Porter (1988) and Hendricks *et al.* (2003), who show how additional information about the common value can help identify the model. My model goes further— if the analyst knows the common value *and* can assume that a component of this common value is common knowledge to the players, the model can be identified even in the presence of errors in pricing (or bidding) decisions and possibly affiliated signals amongst players. This is important in my setting because I am interested in how information quality differs with firm characteristics: if pricing is noisier at some firms than others, I need a way to ensure that this noise is not mistakenly attributed to misinformation. Of course, I examine posted prices and not auction bids. The only paper in industrial organization outside of auctions that estimates information structures of which I am aware is Grieco (2014), who studies entry.[5] In the random choice literature, Lu (2016) studies a single-agent discrete choice problem in which there is choice-specific unobserved heterogeneity and an unknown information structure. He shows that the agent's information structure is identified if the entire random choice rule is observed. My method does not require so much of the data and applies to choices over a continuous variable.

Finally, this paper relates to a number of recent papers in industrial organization focused on the hotel industry.[6] There are two key themes in these papers, both related to the effects of chain affiliation. The first is the importance (and consequences of) demand uncertainty, as examined in various regards by Butters (2017), Cho *et al.* (2018), and Kalnins *et al.* (2017). Some of these papers loosely suggest that chain affiliation can provide an advantage by helping to mitigate uncertainty. The second set of papers is concerned with the importance of quality provision in hotels, with emphasis on vertical differentiation (Mazzeo, 2002), chain affiliation (Hollenbeck, 2017), and provision of amenities (Hubbard & Mazzeo, 2019). Notably,

[4] A recent contribution to this literature by Compiani *et al.* (2018) establishes identification of a common-values auction with a different (non-nested with my model) form of unobserved heterogeneity.

[5] Notably, Magnolfi & Roncoroni (2017) study a mirror-image of this problem. They estimate the payoff parameters of an entry game under weak informational assumptions, as opposed to estimating the information structure itself.

[6] There are also several papers examining the implications of the rise of the sharing economy in hospitality. See, e.g., Farronato & Fradkin (2018).

Hollenbeck (2017) concludes that chains' main advantage is through brand value. Finally, this paper is related to Kalnins *et al.* (2018), who study how heterogeneity in hotel productivity affect the chain's decision to franchise.

2 Background and Data

The Hotel Industry

The U.S. hotel industry generated $185 billion in gross bookings in 2017; the accommodations industry overall accounted for 0.8% of GDP in that year, as compared to 0.7% for air travel.[7] The majority of hotels in the United States are affiliated with a chain. Most chains consist of a parent company (e.g., Intercontinental Hotels Group or Marriott International) and its portfolio of brands (e.g., Intercontinental owns Holiday Inn, Crowne Plaza, and others; Marriott owns Courtyard by Marriott, Fairfield Inn, flagship Marriott hotels, and many other brands). To avoid confusion, I hereafter avoid using the word "chain" unless it is in reference to both the parent company and its portfolio of brands.

Over the past twenty years, these parent companies have divested most of their properties and now own very few properties outright. Roper (2017) discusses this trend in-depth and reports that, of the five largest hotel parent companies in the United States, none outright own more than 8% of their rooms. As a result, chain-affiliated hotels are generally franchised and managed by either the franchisees themselves or third-party management companies. Though the terms of the franchisee-parent company relationship vary across brands, generally the parent company provides branding, training, and information technology; in return the franchisee upholds corporate standards and pays the parent a fixed fee plus a percent royalty off top-line revenues. The royalty rates, in sum, are generally on the order of 10% to 15% and may vary with the way revenues were attained (e.g., via online bookings or direct from the website). Royalty rates vary across brands but not within brand (e.g., across markets). The franchisee is usually the residual claimant on hotel profits.[8]

Parent companies do not engage in resale price maintenance. That is, they delegate pricing to the franchisee or management company. Conversations with industry analysts and

[7] see *bea.gov*

[8] By law, franchisors who operate in Wisconsin must publicly post franchise disclosure documents online. These documents go through, in detail, the legal terms of the standard franchisee contract for a particular hotel brand. See https://www.wdfi.org/fi/securities/franchise/default.htm.

examination of the trade literature suggest a couple of possible reasons why they delegate pricing. First, there is the possibility that franchisees have some "local knowledge" about market conditions that the parent does not have. As established, for instance, in Aghion & Tirole (1997), delegating decision rights to the agent may be desirable in order to provide stronger incentives for the agent to collect information, especially if the agent is best positioned to gather pertinent information. This is true even if the franchisee can be relied upon to truthfully report information upstream in the event that the franchisee does not have the formal authority to make decisions. Second, parents' and franchisees' incentives are generally aligned when setting prices. The only time any such tension is mentioned over the past year in *Hotel Management*, the leading trade publication for hotel franchisees, is in the following quote:

> The brands' business models continue to evolve and they are much more top-line focused in terms of fee income earned...[franchisees] are valued on bottom-line performance...Hotel owners and brands are inextricably linked, but their fortunes may not be. I've often written about an antithetical relationship between the two—what's good for one is bad for the other. Consider supply: Brand companies, in order to grow their stock price, need to show net-unit addition; meanwhile, owners abhor new supply cutting into their margins. It's symbiosis gone wrong.

If marginal costs were nonzero, there would indeed be a wedge between the revenue-maximizing and profit-maximizing prices. However, in the hotel industry, marginal costs for booking additional rooms are very small.[9] In fact, the industry standard for hotel performance is revenue per available room, or "RevPAR", not any measure of net profits. The above quote is more likely describing the wedge between franchisees and parent companies on other margins, such as quality provision and entry. Franchisees may desire to invest less in quality than the franchisor because of brand externalities, or the franchisee may wish to prevent the franchisor from opening additional properties under the same brand, with other franchisees, in the same geographic market.

Although hotel chains do not use resale price maintenance, they typically send price recommendations on a continuing basis to their franchisees. Though exact practices vary by chain, region, or even establishment, usually a parent company will have a centralized revenue management group that monitors demand in a group of markets (often, a revenue management

[9]For instance, in his popular memoir about managing hotels, *Heads in Beds*, Tomsky (2012) estimates that the marginal cost of booking a room at a luxury hotel is around $35 but much lower at midscale hotels. However, this estimate is based on costs of "cleaning supplies, electricity, and hourly wage[s]" for workers. A sizable proportion of these costs are incurred whether the room is booked or not.

office is assigned to a particular region). Franchisees have access to some proprietary revenue management system operated by the parent company's revenue management office. Through this system, the parent's revenue management team sends price recommendations to franchisees on a continuing basis throughout the booking window. These recommendations are not binding, nor is there any sort of punishment for ignoring them,[10] but they may convey some information or insight the chain has been able to gather about market conditions. It is through this process that there may be scope for chains with better data or more sophisticated IT capabilities to price more effectively.

The algorithms or heuristics parent companies use in generating these price recommendations, particularly their methods of forecasting demand, are largely a "black box" and vary across chains and possibly geographic markets. Furthermore, franchisees may be able to collect information about market demand beyond whatever is conveyed to them by the parent company. There remains a notion that franchisees' "local knowledge" is important in the industry. The extent to which franchisees are able and willing to collect information about evolving market conditions is surely heterogeneous. A study by Köseoglu *et al.* (2016) conveys, in more detail, how information-gathering practices vary among hoteliers. This study suggests that hoteliers, while clearly able to gauge market demand to some extent through their own demand, struggle to find out what their rivals are doing in real time. One illustration is as follows:

> Several hotel managers gather information about other hotels via the Internet (e.g., hotel websites, Expedia.com, social media, etc.), reporting services to which they subscribe (e.g., Star Reports, Hotelligence, etc.), and "drive arounds" (i.e., driving around looking for corporate vehicles in the parking lots of competitors) [...] A few respondents indicated that they call other hotels, either identifying themselves or engaging in mystery shopping.

Notably, "Star Reports" are provided by the same company and based on the same data I use in this analysis. Based on these insights, I model hotels as able to see their own demand realization, but imperfectly informed about market demand and rivals' behavior. Hotels price in response to both— their own demand draw, and (an aggregate of) their rivals' prices— but cannot fully distinguish between what is common to all hotels or idiosyncratic to only themselves.

[10] There are no stipulations in franchisee disclosure documents mentioning any responsibility to price in accordance with the chain's wishes. In my conversations with those who work in the industry, there is no notion that "lone wolf" pricing is punished. Franchisee contracts may be unilaterally terminated, but only on the basis of failure to uphold corporate quality standards, negligent or dishonest behavior, etc.

Data

My main data source is STR, Inc., a hotel benchmarking company that collects price and occupancy data from its member hotels and offers members competitive reports on pricing and performance. STR's coverage is quite extensive; their database includes over 90% of chain-affiliated hotels in the United States. Table 1 provides a sense of coverage in my geographic markets by comparing property counts in my data to those reported by the Census Bureau. Most hotels use STR's services as a way to gauge their performance against their "comp set"—typically, a group of rivals in the same quality tier and geographic market. Reports about the "comp set" include the Star Reports mentioned in the previous subsection.

An observation in my dataset is a hotel on a given night. My dataset includes the average daily rate (or ADR, which I hereafter use interchangeably with "price") and occupancy rate for each hotel-night across eighteen different U.S. markets for a calendar year, between July 2016 and June 2017. I also have information about hotel characteristics, namely the anonymized franchisee, brand, management company, and parent company, as well as quality tier and capacity. I do not observe individual booking data. As a result, I do not know how far in advance rooms were booked, through what channel they were booked, and the degree to which price dispersion exists for a specific hotel on a specific night.

My eighteen markets are all United States college towns with relatively large student populations, prominent Division IA football teams, and a degree of isolation from other, larger metropolitan areas. I choose these markets because their boundaries are easily defined (as compared to, for instance, Evanston as part of Chicago), and it is easy to identify particular nights on which market-level demand for lodging will be high. These nights are the nights before and after undergraduate move-in, graduation, and home football games, which I identified using online search. I flag these as "high demand days" in my data. The hotels in my data are all within fifteen miles of the college's stadium, though most of these are actually within a five mile radius of the stadium.

Finally, I match the hotels in my dataset to the *2015/16 HVS Franchise Fee Guide*. HVS is a consulting firm that specializes in hotel management; the franchise fee guide is designed as a tool to help franchisees assess which brand is right for them. The fees are compiled by reviewing franchisee disclosure documents and are reported as percentages of expected annual revenues for that brand. Though most brands levy royalties as percentages of revenues, some brands instead charge a flat annual or per-room fee. I identify these brands using additional details in *Hotel Management Magazine*'s franchise fee guide, which collects less comprehensive

Table 1: Geographic markets in data

Market	Properties in Data	Census	Market	Properties in Data	Census
Ann Arbor, MI	75	44	Knoxville, TN	108	76
Auburn, AL	28	26	Madison, WI	79	83
Bloomington, IN	21	21	Oxford, MS	9	10
College Station, TX	43	43	South Bend, IN	59	44
Columbia, MO	29	34	Starkville, MS	11	13
Columbia, SC	97	77	State College, PA	28	26
East Lansing, MI	35	46	Tuscaloosa, AL	33	34
Gainesville, FL	33	38	Urbana-Champaign, IL	35	38
Iowa City, IA	26	29	West Lafayette, IN	20	27
Total					768

Source: STR, Inc. and U.S. Census Bureau *County Business Patterns* 2016. STR data include all hotels in data within fifteen miles of campus. Census data reported for county in which market is primarily located. Because these market definitions do not exactly coincide, either figure may be larger than the other. However, because most markets in my dataset are relatively isolated, these discrepancies are generally small. An exception is Ann Arbor; my dataset includes some properties to Ann Arbor's east as part of Wayne County in the Detroit metropolitan area.

information on franchise fees but reports whether they vary with revenues. Brands that charge flat fees (and independent hotels) are recorded as having a 0% marginal royalty rate on revenues in my analysis.

Because most of my analysis focuses on differences across parent companies, I report summary statistics of my data by parent company in Table 2. For confidentiality reasons, parent company is anonymized in my data. As is the case in the United States at large, five parent companies collectively dominate these markets, with a competitive fringe consisting of many smaller parents and independent hotels. I refer to these parent companies as the "large parents" throughout this paper. Of these parent companies, two ("A" and "B") exist primarily in higher-quality tiers, one ("C") is primarily midscale, and two ("D" and "E") are primarily lower-quality. I refer to "A" and "B" as "upscale large parents" at times in this paper and to "C", "D", and "E" as "downscale large parents". Franchisees affiliated with the two large upscale parent companies in particular generate more revenue per available room, charge higher prices, and usually fill more occupancy than their rivals.

I also report differences across parent companies in their marginal royalty rates in Table 3. Of the 768 hotels in my dataset, I was able to match 729 of them to a marginal royalty rate, including the 28 independent hotels assigned a marginal royalty rate of 0%. In general,

Table 2: Data summary, by parent company

Parent	Number of Hotels: Upscale	Midscale	Downscale	Total	Mean: ADR ($)	Occupancy (%)
A	9	97	0	106	122.92	73.37
B	12	94	0	106	118.45	70.67
C	1	79	15	95	104.57	68.41
D	0	58	86	144	77.60	58.08
E	0	5	119	124	68.42	52.66
All Other Parents	1	53	111	165	78.26	64.81
Independent	16	7	5	28	122.11	59.88
Total	39	393	336	768	93.03	63.81

Source: STR, Inc. "Upscale," "Midscale," and "Downscale" classifications based on STR classification of hotel segments. STR reports six different quality tiers, I coarsen these tiers into three. Mean ADR and Occupancy calculated as average across all hotel-nights in dataset.

the larger parent companies charge higher royalty fees than their rivals. Because franchisees are residual claimants on profits net of these fees, this implies that franchisees have higher-powered incentives to gather information, insofar as this information allows the franchisee to maximize revenues, at smaller chains, all else equal. Though these differences do not seem especially large, I will show in my counterfactuals that they are capable of explaining a large amount of variation in franchisee information by influencing franchisee effort.

Overall, price and occupancy are positively correlated in my data. This is consistent with the general notion that, in the hotel industry, the main source of variation from one night to another is in demand. As a result, variation in demand can be thought of as tracing out an upward sloping reduced-form supply schedule. The binned scatterplot in Figure 1 demonstrates that this relationship. Each point in the plot conditions on a hotel fixed effect. Therefore, the figure does not reflect any correlation between price and occupancy that may occur across different hotels. The upward-sloping line formed by these points is also convex, consistent with the "hockey stick" shape common in settings where capacity constraints are present. As occupancy nears 100%, price increases rapidly in order to allocate the remaining capacity in a way that maximizes revenue. This suggests that a key driver of price increases in the industry is the opportunity cost of capacity (though this is not conclusive; this pattern is consistent with other stories as well).

Table 3: Marginal royalty fees by parent company

Parent Company	Avg. Margnal Royalty (%)
A	13.65
B	12.67
C	13.13
D	11.24
E	12.54
All Other Parents	9.13
Independent	0.0
All Hotels	11.45

Source: STR, Inc. and *HVS 2015/216 Franchise Fee Survey.* For brands whose royalty fee is levied as a percentage of total revenues, the marginal royalty is equal to the percent royalty reported by HVS. For brands whose royalty fee is levied as a fixed rate (e.g., dollars per room per month), HVS reports royalties as an expected percentage of annual revenues; I record the *marginal* royalty as 0%.

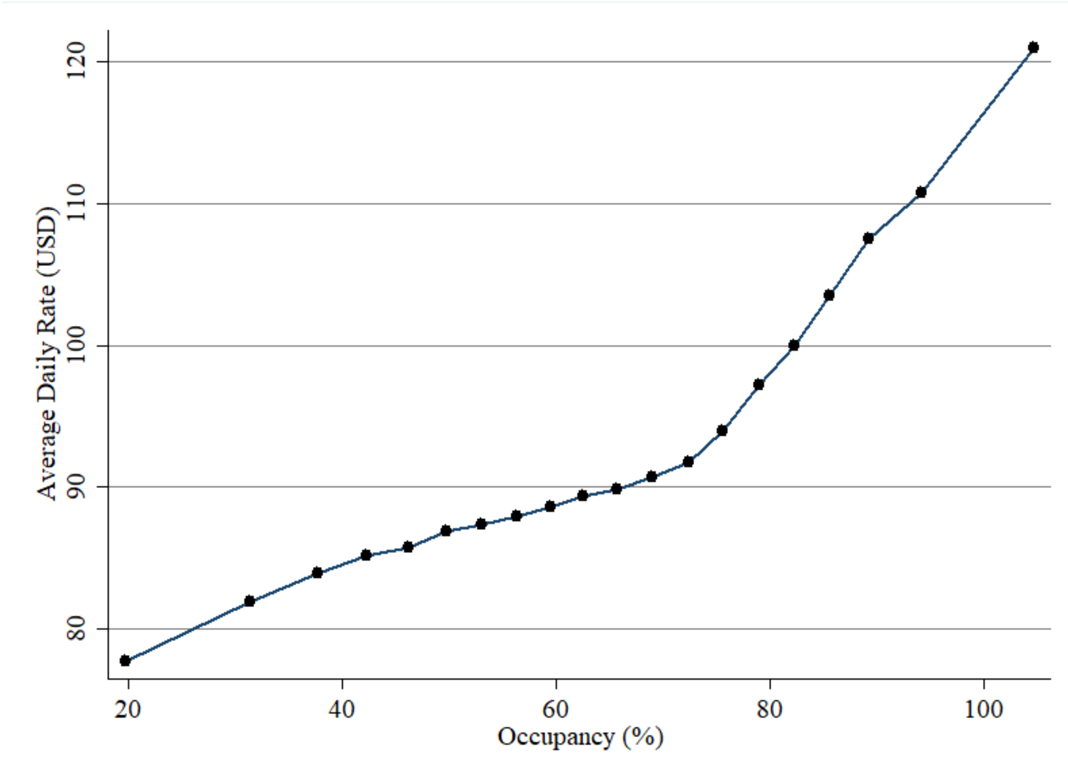
Descriptive Evidence of Imperfect Information

I now present evidence that suggests that hotels have imperfect information about demand when they set prices. In order to gain some intuition, I describe a highly simplified setting that supposes that, under perfect information, hotels' reduced-form supply schedule reflects the shape of the binned scatterplot in Figure 1. Suppose a hotel faces a downward sloping residual demand curve that is governed by a demand state D. As D increases, the residual demand curve shifts outwards. For simplicity, suppose D could only take two values with equal probability, D_{low} and D_{high}, with $D_{low} < D_{high}$.

This setting is depicted in Figure 2. According to the supply schedule, the higher the hotel's beliefs over D, the higher the price it sets. Suppose the analyst had information about price and occupancy for a number of nights, each an independent draw of D. The first panel shows what the analyst would observe if the hotel had perfect information; that is, it shows what the outcomes would be if the hotel always knew D. Price and occupancy would be positively correlated, with half of all nights at point A_{low}, and half of all nights at point A_{high}. If we were to fit a line to this data, it would have an upward slope and pass through both of these points. This is the red dashed line in panel (a).[11] Call this line of best fit the "price response

[11] More demand states would trace out the supply schedule, causing our price response curve to be misspecified insofar as the supply schedule is nonlinear.

Figure 1: Binned scatterplot, price vs. occupancy



Source: STR, Inc. Binscatter plot of average daily rate on occupancy, after absorbing hotel-level fixed effects.

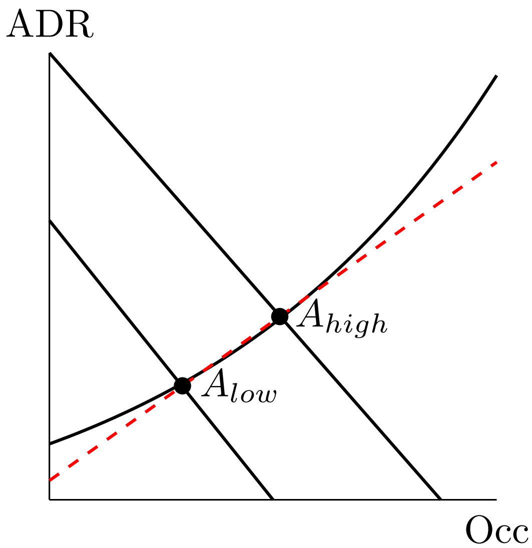
curve" under perfect information.

Next, suppose the hotel had no information about demand. All it knew was that the two demand states were equally likely, and this was all it knew regardless of the actual demand state. We would reasonably expect the hotel to choose a price somewhere between the prices at A_{low} and at A_{high}, though the most important feature is that, if the hotel's beliefs don't change, it always chooses the same price. As a result, we would expect only occupancy to vary. The analyst would observe data points B_{low} and B_{high} with equal frequency. If we were to fit a price response curve to this data, it would be flat, as is the dashed line in panel (b).

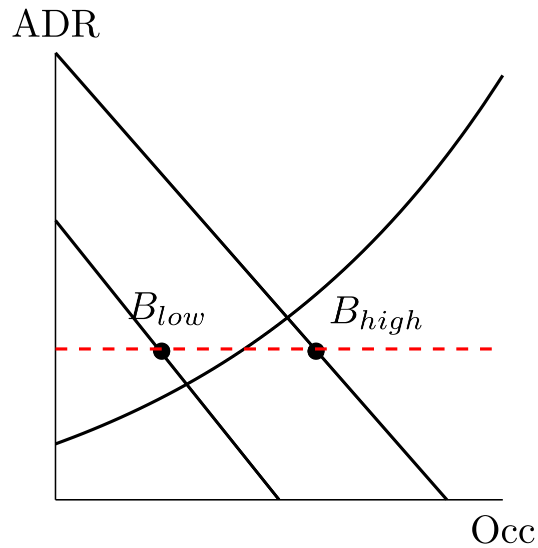
Finally, suppose the hotel had an intermediate quality of information: sometimes, it knew the demand state, but sometimes, it maintained the same (uninformed) beliefs that led it to set the price at B_{low} and B_{high}. Though this is not how I model information quality in Section 3, it is the cleanest way to depict information quality in this setting. In this case, the analyst would observe data at all four points: A_{low}, A_{high}, B_{low}, and B_{high}. If we were to fit a price response curve to this data, it would slope upward, but less so than in the perfect-information

Figure 2: Price response curves

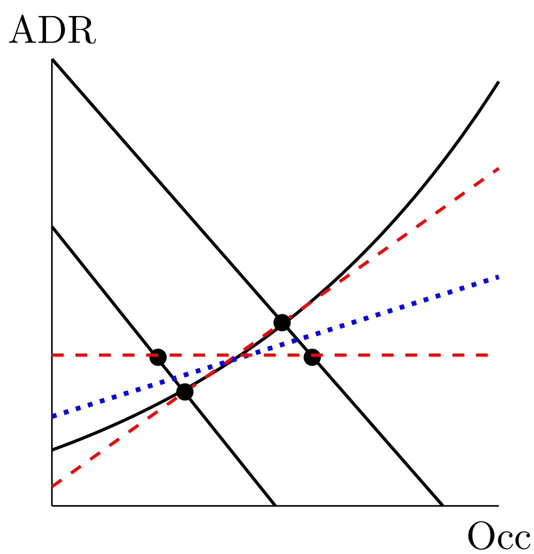
(a) Perfect information



(b) No information



(c) Imperfect information



case. The relative frequency of A observations versus B observations would depend on how frequently the hotel were informed; the better the information, the more A points in the data, and the steeper the price response curve. The case in which all four points are observed with approximately equal frequency, and the (blue, dotted) price response curve associated with this setting, is depicted in panel (c) of Figure 2.

Note that the price response curve does not need to accurately reflect the supply schedule. It also does not need to exactly identify the quality of information the hotel has; I leave that for the more formal treatment in Section 3. However, the argument I just outlined is similar to my identification strategy. For the purposes of this section, all that matters is that the line of best fit is steepest for perfect information and flatter if information is worse. Note that this strategy does not require the analyst to measure how large the demand shifts are. A larger demand shift would lie further along this price response curve, but would not substantially change the curve itself.

I analyze my data based on this discussion. I construct a price response curve that is based only on variation in demand shifters that I assume are easily predicted, such as a home football games or day of the week. I then construct a price response curve that is based only on variation that is not necessarily as easily predicted; specifically, I construct the price response curve based on all variation in market-wide demand *conditional on* the predictable demand shifters.

I first estimate the following regressions, where j indexes a hotel and t indexes a city-night:

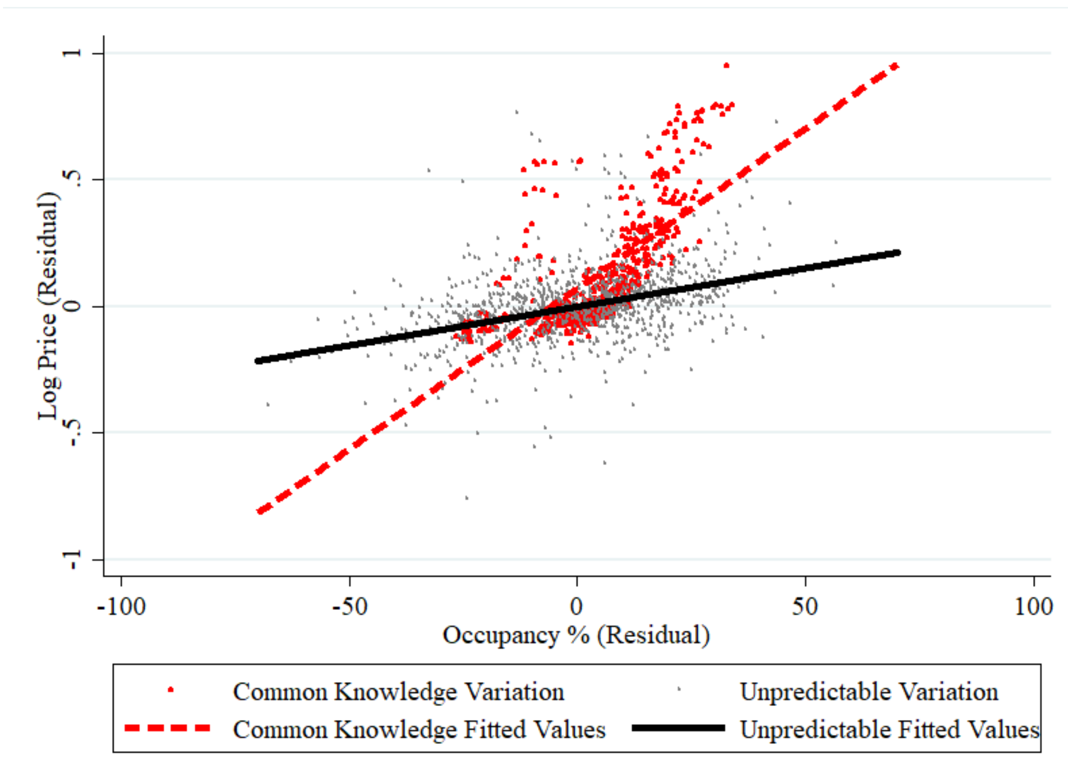
$$\begin{aligned} \log(ADR_{jt}) = &\quad \lambda_j^p + \beta^p x_{jt} + u_{jt}^p \\ Occupancy_{jt} = &\quad \lambda_j^q + \beta^q x_{jt} + u_{jt}^q. \end{aligned} \tag{1}$$

λ_j is a hotel fixed effect. x_{jt} includes dummies for a hotel's brand interacted with a weekday indicator (i.e., a dummy equal to one if it is a Friday through Sunday), the city interacted with day of week, and the city interacted with status as a flagged high demand day. All of the variables in x_{jt} are easily predicted by the hotel; the variation that drives residuals u_{jt} may not be. Having estimated these regessions by OLS, the "predictable" part of prices and occupancy, conditional on hotel fixed effects, is thus

$$\begin{aligned} \widehat{\log(p_{jt})} = &\quad \hat{\beta}^p x_{jt} \\ \widehat{Occupancy}_{jt} = &\quad \hat{\beta}^p x_{jt}. \end{aligned}$$

The "unpredictable" components of prices and occupancy are $\hat{u}^p_{jt}$ and $\hat{u}^q_{jt}$ respectively. I plot these points, as well as lines of best fit, in Figure 3. These lines of best fit correspond to the price response curves in the theoretical discussion. The dashed line corresponds to variation coming from common knowledge demand components; the solid line corresponds to variation coming from sources that are not necessarily common knowledge. The solid line is flatter, consistent with hotels not having perfect information about this demand variation.

Figure 3: Descriptive evidence of imperfect information



Data source: STR, Inc.

Notably, this strategy resembles the Chiappori & Salanié (2000) test for the presence of private information. They regress a choice variable (in my setting, prices) on observables, and an outcome variable (in my setting, occupancy) on observables. Correlation in the errors indicates that the decision is responding to something beyond what is observed to the econometrician. That is, correlation in the two errors (in my setting, an upward sloping price response curve) indicates that the decision makers (hotels) have information (about demand) beyond what is measured in observables (x_{jt}). My analysis takes the further step of comparing the correlation in the errors to correlation in the part that can be explained by observables. If we are willing to accept that prices should respond observables and unobservables (e.g., predictable and unpredictable demand shifts) the same way under perfect information, then the slopes of these two lines should be approximately the same.

This assumption—that both sources of demand variation should yield the same price response under perfect information—is not easy to assess in this descriptive analysis. In Sections 3 and 4, I provide a stronger basis for this assumption by measuring demand shifts as elements of a utility index in a nested logit demand system. There are other reasons for a model: this analysis does not account for the fact that price and occupancy directly affect one another, prices and occupancy may also depend on rivals' choices and information, and the errors in equations 1 may capture variation in addition to that arising from unpredictable demand shifts.

3 Nonparametric Identification of Information

I now present my identification strategy for the supply side of the model, which can be estimated sequentially, after demand has been estimated. I will return to demand in section 4. This section lays out how I leverage both within-firm variation in prices and demand over time, as well as cross-firm co-variation in prices, to identify my model of supply. This model has several key features:

- Hotels have incomplete information about a market-wide demand shift but receive a signal about demand. This signal, modelled as a joint distribution over thw market-wide demand shifter and the signals hotels receive, does not have a particular parametric specification, but merely obeys some monotonicity restrictions.
- Hotels also receive private demand draws. These draws are imperfectly correlated across hotels, because they contain both the common demand state and a hotel-specific demand draw.
- Hotels formulate beliefs about the market-wide demand shifter based on their own demand draws as well as the signal they receive. Hotels choose prices in response to their rationally-formed beliefs over rivals' average prices. Hotel price policy functions, which map what hotels do observe about the market to the prices they choose, can be heterogeneous across hotels and are modelled fairly flexibly.
- Price data may be contaminated by an i.i.d. error for each hotel-night. That is, hotels price noisily.

The key to identification is that one component of this common demand state is common knowledge to all hotels. By comparing the responsiveness of prices to this common-knowledge shifter and the imperfectly known common demand state, I can recover information quality. The general idea is that, all else equal, the larger the wedge between firms' response to the unobserved shifter and the observed shifter, the less informed firms must be. This is analogous to the wedge described in the previous section.

A Simple Example

To gain some intuition for this approach, consider a highly simplified, single-hotel example. The market demand state is $\theta = \theta^{known} + \theta^{unknown}$, where the hotel knows θ^{known} but not $\theta^{unknown}$. A signal is drawn according to $F(s, \theta^{unknown})$. Suppose $F(s|\theta^{unknown})$ is stochastically increasing in $\theta^{unknown}$ (e.g. FOSD or MLR-ordered) so that posterior beliefs over $\theta^{unknown}$ are higher whenever s is higher. Assume that θ^{known} and $\theta^{unknown}$ are independent. On each date t, the hotel sees this signal as well as θ^{known}, and sets prices according to

$$\begin{aligned} p_t &= z\mathbb{E}(\theta_t|s_t, \theta_t^{known}) + \nu_t \\ &= z\mathbb{E}(\theta_t^{known} + \theta_t^{unknown}|s_t, \theta_t^{known}) + \nu_t \\ &= z\theta_t^{known} + z\mathbb{E}(\theta_t^{unknown}|s_t) + \nu_t \end{aligned}$$

where $z > 0$ is some parameter and ν_t is i.i.d. mean-zero noise distributed $\mathcal{N}(0, \sigma^2)$.

Suppose first that the analyst observes p_t and θ_t for many t but not the components θ_t^{known} and $\theta_t^{unknown}$. A naive approach would be to regress prices on θ and hope that the coefficient will be a consistent estimator for z. Amongst other concerns, such a regression will be misspecified because, without further structure on F, $\mathbb{E}(\theta|s, \theta^{known})$ is not guaranteed to be a linear function. If the analyst instead ran a nonparametric regression of prices on θ,

$$p_t = \hat{Z}(\theta_t) + \hat{\nu}_t, \tag{2}$$

it would be impossible to map $\hat{Z}(.)$ onto (z, F). For instance, $\hat{Z}(.)$ may be very flat if z were small (i.e., the firm does not respond much to θ), or if variation in θ came mostly from $\theta^{unknown}$ and F was very uninformative (i.e., the firm is not aware of variation in θ). Put succinctly, "I don't know (about θ)" is observationally equivalent to "I don't care (about θ)."

A second approach may be to try to recover F from the distribution of noise $\hat{\nu}$ in regression 2. However, this is also impossible: the noise in the data come from different sources that are impossible to disentangle here. There is signal-generated noise from $F(s, \theta^{unknown})$ and idiosyncratic noise from ν. As a result, a noisy signal or a large variance in ν may also be observationally equivalent (and this is in fact true even if we observed $\theta^{unknown}$).

If, instead, the analyst observed $\theta^{unknown}$ and θ^{known} separately, the model parameters are identified. The analyst could instead execute the semiparametric regression

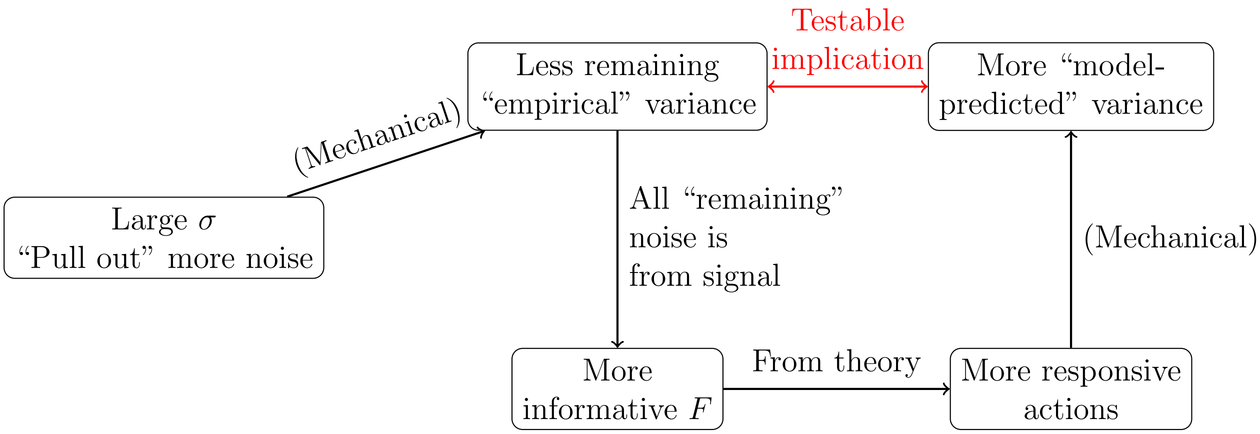
$$p_t = \hat{z}\theta_t^{known} + \hat{Z}(\theta_t^{unknown}) + \hat{\nu}_t.$$

Because the signal does not depend on θ^{known}, this regression is correctly specified, and $\hat{z}$ is consistent for z. Recovering F is more involved because it affects both $\hat{Z}$ and the distribution of $\hat{\nu}$. Figure 4 provides a schematic outline of how identification is achieved here. I conducts a more detailed and formal discussion of how F is recovered in the next subsection, but I will outline some intuition here.

Suppose we incorrectly guessed $\sigma = 0$, so we attributed **all** of the noise in $\hat{\nu}$ to the signal. That is, any variation in prices, conditional on θ^{known}, must have come from different signal realizations. This would imply a relatively uninformative (i.e., noisy) signal. As a result, we would expect $\mathbb{E}(\theta^{unknown}|s)$ to respond minimally to changes in s, and so, conditional on θ^{known}, prices would not vary much, because beliefs do not vary much. But this contradicts our assertion that, because $\sigma = 0$, prices are very noisy.

If we instead guessed σ, the standard deviation of ν_t, was too large, this would imply a stronger (less noisy) signal because less noise remains in the data after "taking out" the noise induced by ν. Then the opposite would hold: beliefs would respond strongly to signals, so, conditional on θ^{known} and, prices would vary a lot. This notion— that chosen actions display more variance when information is better— is an implication of recent results in economic theory (Vizcaíno & Mekonnen, 2019). In this case, the theoretical prediction that prices would vary greatly conditional on θ^{known} again contradicts our assertion that, net of the noise we "took out," prices do not vary much conditional on θ^{known}. As the next subsection makes more formal, in a more general setting, it turns out that there is a single value of σ for which the amount of noise, conditional on θ^{known}, that remains in the price data after "pulling out" ν equals the amount of noise implied by the signal. This pins down both F and σ.

Figure 4: Schematic of identification of signal structure



Identification

I now establish identification in a more general model. Index hotels in a city as $j = 1, 2, \ldots, J$ and the set of all hotels in the city as $\mathcal{J}$. Index time as t. Suppose I have identified demand for each j and t (e.g., in a multinomial or nested logit), giving me estimates of mean utility for each hotel-night in the data.[12] Call this mean utility

$$\delta_{jt} = x_t + \lambda_t + \xi_{jt}.$$

where x_t is a market-wide, common-knowledge demand shifter, λ_t is a market-wide, incompletely known demand shifter, and ξ_{jt} is a hotel-specific, unobserved demand shifter. x_t can be thought of as salient features of that particular market-date, such as whether it is a weekday or a home football game. λ_t can be thought of as a nightly fixed effect, and ξ_{jt} can be thought of as a residual (e.g., the unobserved heterogeneity in a Berry *et al.* (1995)-type model). If demand is identified, all of these demand shifters are known to the econometrician. At the time it chooses prices, the hotel observes x_t and δ_{jt} but cannot fully disentangle λ_t from ξ_{jt}. That is, hotel j does not observe λ_t or ξ_{jt}. It is most natural to think of δ_{jt} as a hotel's private demand draw; these draws may be correlated across hotels because of the common components. I now delineate key assumptions I maintain throughout my analysis.

[12] I am abstracting from unobserved heterogeneity in consumer tastes, e.g., mixed logit. In such a case, I could assert that x_t and λ_t are averages across all consumer tastes, though this assumption is potentially problematic, as the consumers most "relevant" to a particular hotel, and thus their tastes, may vary with the hotel's chosen price. Accordingly, I work with nested logit does not face this problem while still allowing for heterogeneous substitution patterns. I discuss identification of demand in the next section; as usual, it relies on supply-side instruments for prices and shares.

Assumption 1. Information. x_t is common knowledge. δ_{jt} is private knowledge of hotel j. Let $F(\mathbf{s}, \lambda | x, \{\delta_{jt}\}_j) = F(\mathbf{s}, \lambda)$ be the joint distribution of every hotel's signal and λ_t, where $\mathbf{s}_t = \{s_{jt}\}_{j \in \mathcal{J}}$ is the entire vector of signals for all hotels on night t.

I impose the assumption that the signal structure is independent of the other demand variables. The signal is thus a way to capture the hotel's information about the *commonality* of demand shocks. That is, a hotel knows its own demand draw δ_{jt}; it does not perfectly know whether this demand draw is market-wide or idiosyncratic.

Though hotels privately observe their signals, these signals are allowed to be arbitrarily correlated across hotels conditional on λ_t, so long as they are affiliated. There are two reasons why hotels may have correlated information about demand shocks, even conditional on λ_t. The first is that two hotels, especially those belonging to the same chain, will set similar prices because they are obtaining information from the same source; it is important to note, however, that two hotels from the same chain may not have perfectly correlated information because franchisees may conduct their own market research. Second, hotels may have "spuriously" correlated information because the tools, practices, or rules-of-thumb revenue managers use, while on average correct, may lead to the same biases in demand forecasts on a particular day.

Assumption 2. Demand variables. I assume λ_t and ξ_{jt} are not serially correlated. This precludes firms from making inferences about demand on date t based on information about date $t-1$. Furthermore, I assume ξ_{jt} is independent of the other demand shifters; in my application, this follows from the identifying assumption for demand: product unobservables are independent of the exogenous variables, including the other demand shifters.

Assumption 3. Pricing policy. Hotel j chooses prices according to the following rule:

$$p_{jt}(x_t, \delta_{jt}, s_{jt}, \nu_{jt}) = z_{0j} + z_{pj}\mathbb{E}(\bar{p}_{-jt} | x_t, \delta_{jt}, s_{jt}) + z_{\delta j}(\delta_{jt}) + \nu_{jt}$$

where $\bar{p}_{-jt} = \frac{1}{J-1} \sum_{j' \in \mathcal{J}/j} p_{j't}$ is the average price of all of j's rivals and ν_{jt} is an i.i.d. pricing error distributed $\mathcal{N}(0, \sigma_j^2)$. z_{pj} is assumed to be positive and small enough for a solution to the joint pricing decision for all firms to exist,[13] and $z_{\delta j}(.)$ is assumed to be increasing. Notably,

[13] A sufficient condition is that the following matrix Z is positive definite:

$$\begin{bmatrix} 1 & -\frac{z_{p1}}{J-1} & \dots & -\frac{z_{p1}}{J-1} \\ -\frac{z_{p2}}{J-1} & 1 & \dots & -\frac{z_{p2}}{J-1} \\ \vdots & \vdots & & \vdots \\ -\frac{z_{pJ}}{J-1} & -\frac{z_{pJ}}{J-1} & \dots & 1 \end{bmatrix}.$$

this imposes that pricing is:

1. *Aggregative*: prices depend on rivals' prices through their average only. That is, hotel j treats rivals j' and j'' symmetrically.

2. *Invariant to dispersion*: prices only depend on *expected* rivals' average prices. Dispersion (and other moments) of rivals' prices do not matter.

3. *Linearly separable*: prices are affine in expected rivals' average prices and separable between rivals' prices and own demand.

4. *Monotone*: prices are strictly increasing in both own demand draw and expectations of rivals' prices.[14]

Note that δ_{jt} can also serve as a signal for rivals' prices because it contains λ_t, but s_{jt} may provide additional information that separates λ_t from ξ_{jt}. Distinguishing between changes in λ_t and ξ_{jt} are important because only increases in λ_t will increase rivals' prices in expectation.

I depart from standard practice by directly assuming a reduced-form price policy function, rather than fully specifying a structural model of hotel costs and objectives. Because hotel pricing is a complicated revenue management problem, standard oligopoly models of supply do not even yield the correct comparative statics on even simple matters such as whether mergers decrease output (Kalnins *et al.* , 2017). A fully structural supply model is thus likely to be misspecified. See the end of this section for a more detailed discussion of this modelling choice.

Assumption 4. Signal monotonicity. Higher signals yield higher beliefs over λ_t, and, by the assumed monotonicity of the pricing rule, also rivals' prices. For instance, $F(s_j|s_{-j}, \lambda)$ may be MLR-ordered in λ for each j, and $(s_j, s_{j'})$ are weakly positively correlated conditional on λ for each pair of firms in the market. Fixing x_t and δ_{jt}, the higher the signal, the higher the hotel's beliefs about λ_t and the lower its beliefs about ξ_{jt}. [15]

[14] Relaxing most of these conditions would fundamentally change the identification strategy. In the case of removing monotonicity, this would likely result in non-point identification. Linearity (though not separability) can almost certainly be relaxed, with a few modifications; this generally involves building the restrictions later in this section (see: equation 7) in accordance with the more involved definitions of "responsiveness" outlined in Vizcaíno & Mekonnen (2019). Because of their attractive properties regarding tractability, linear separability, aggregation, and invariance to dispersion are common assumptions made in theoretical and empirical studies of games of incomplete information. For instance, Angeletos & Pavan (2007) study a class of quadratic games that have similar properties to this.

[15] See Athey & Levin (2018) for a discussion of paired assumptions on payoff and information structures that guarantees monotonicity; the stronger the imposed assumptions of complementarity between the action and the state, the weaker the assumption needed on information structures.

Assumption 5. Data. The analyst observes the full joint distribution of prices and demand shifters: $\{p_{jt}, \lambda_t, x_t, \xi_{jt}\}_{j,t}$. Let $G(.)$ denote the joint distribution over all of these variables. Note that this immediately implies δ_{jt} is as good as observed by the analyst.

Proposition. Under **Assumptions 1-5**, the supply model, $\{z_{\delta j}, z_{pj}, \sigma_j\}_{j\in J_t}$ and F, is identified.

First, consider one hotel j at a time and suppress subscript t. Let $\hat{p}_j(\delta_j, x, s_j) = p_j(\delta_j, x, s_j, 0)$. That is, it is j's price without the idiosyncratic noise. Consider the expectation of j's prices conditional on a realization of the demand variables x and δ_j:

$$\mathbb{E}(p_j|x, \delta_j) = \int \hat{p}_j(\delta_j, x, s_j) dF_j(s_j).$$

This expectation can be directly computed from the data. Then differentiate with respect to x:

$$\begin{aligned} \frac{\partial \mathbb{E}(p_j|x, \delta_j)}{\partial x} &= \int \frac{\partial}{\partial x}\hat{p}_j(s_j, x, \delta_j)\; dF_j(s_j) \\ &= \int z_{pj}\frac{\partial \mathbb{E}(\bar{p}_{-j}|s_j, x, \delta_j)}{\partial x}\; dF(s_j). \end{aligned} \tag{3}$$

The second line is obtained by plugging in the pricing policy function; the only term that varies with x is the term that includes beliefs over rivals' prices. Because the information structure is common knowledge, by the law of total probability, j's beliefs over rivals' average prices is, on average, correct. This means that equation 3 can be written as

$$\begin{aligned} \frac{\partial \mathbb{E}(p_j|x, \delta_j)}{\partial x} &= \int z_{pj}\frac{\partial \mathbb{E}(\bar{p}_{-j}|s_j, x, \delta_j)}{\partial x}\; dF_j(s_j) \\ &= z_{pj}\frac{\partial}{\partial x_t}\mathbb{E}(\bar{p}_{-jt}|x, \delta_j). \end{aligned}$$

As with the left hand side, the expectation on the right hand side (and its derivative with respect to x) can be computed directly from the data. It follows that z_{pj} is identified. This can be done similarly for each j. It should be noted that this step relies on changes in x, holding δ_j constant. That is, if x increases, it is counteracted by a decrease in ξ_j.

Now, I turn to identification of the amount of noise and the signal structure by using variation in the demand variables and prices over time. Consider one hotel j at a time and suppress subscript t, and consider the distribution of j's prices, conditional on x and the entire vector of δ, $G(p_j|x,\delta)$. The variation in p_j in this distribution has two potential sources:

1. Variation in beliefs induced by signal s_j.

2. Idiosyncratic noise, ν_j.

Guess a candidate amount of idiosyncratic noise, $\hat{\sigma}_j$, and deconvolve it from this distribution; that is, "remove" this noise from the distribution of prices in the data. The "noiseless" distribution $\hat{G}_{\hat{\sigma}_j}(\hat{p}_j|x,\delta)$ can be obtained by inverting the following functional equation:

$$F(p|x,\delta) = \int_{-\infty}^{\infty} \hat{G}_{\hat{\sigma}_j}(\hat{p}_j - \nu_t|x,\delta)h_{\hat{\sigma}_j}(\nu_j)d\nu_j \tag{4}$$

where $h_{\hat{\sigma}_j}$ the pdf of normal distribution $\mathcal{N}(0,\hat{\sigma}_j^2)$. I now show that the "noiseless" distribution $\hat{G}_{\hat{\sigma}_j}(\hat{p}_j|x,\delta)$ is enough to recover a candidate signal structure for j. By monotonicity, a higher signal s_j yields higher $\hat{p}_j$, for any given value of x and δ_j. This means that the probability of $\hat{p}_j$ being less than some arbitrary p is equal to the probability that s_j is less than $s_j(p;x,\delta_j)$, where $s_j(.;x,\delta_j)$ is an increasing function of p. That is,

$$\hat{G}_{\hat{\sigma}_j}(p|x,\delta) = Pr(s_j \leq s_j(p;x,\delta_j)|x,\delta). \tag{5}$$

Furthermore, because the distribution of s_j is assumed to be independent of x and δ, we can normalize the distribution of s_j to be uniform conditional on x and δ. That is, the right hand side of equation 5 is uniform on $[0,1]$ without loss of generality.[16] This immediately gives me a mapping from (deconvolved) prices to signals, $s_j(.;x,\delta_j)$. Now, condition on λ. Given our guess of $\hat{\sigma}_j$, we can use this mapping to transform $\hat{G}_{\hat{\sigma}_j}$ into a candidate marginal signal structure:

$$\hat{G}_{\hat{\sigma}_j}(\hat{p}_j|x,\delta,\lambda) = \hat{F}(s_j(\hat{p};x,\delta_j)|\lambda). \tag{6}$$

Furthermore we can represent any deconvolution as a sequence of deconvolutions in the following sense: If $\hat{\sigma}_j = \hat{\sigma}_1 + \hat{\sigma}_2$, we can obtain $\hat{G}_{\hat{\sigma}_j}$ by inverting an equation similar to equation 4

[16]Because $s_j(;x,\delta_j)$ only depends on δ_j, while the right hand side of equation 5 must be uniform for all vectors δ, the model is actually overidentified. That is, if the distribution of p_j was different for two different values of $\delta_{j'}$, $j' \neq j$, the model would be rejected. This restriction roughly says that j's price cannot depend on a rival's private demand shock. In future work, I aim to examine how these restrictions may allow me to estimate a richer model.

with F on the left hand side and $h_{\sigma_1}(.)$ on the right to obtain $\hat{G}_{\sigma_1}$, and then such an equation again with $\hat{G}_{\sigma_1}$ on the left and $h_{\sigma_2}(.)$ on the right.[17] Examining equation 6, we see that each successive deconvolution implies that the implied signal on the right hand side becomes more informative in the Blackwell order.

Vizcaíno & Mekonnen (2019) show that, in supermodular games and monotone decision problems, a more informative signal structure implies that actions become more "responsive." In this setting, in which j's prices are affine in the expectation of rivals' average price, different levels of responsiveness correspond to different amounts of variance in p_j, conditional on λ. That is, fixing all other parameters, call the variance in p_j generated in the model by a particular value of $\hat{\sigma}_j$, $\text{var}_{\hat{\sigma}_j}(\hat{p}_j|x,\delta)$. The condition implied by Vizcaíno & Mekonnen (2019) is that $\text{var}_{\hat{\sigma}_j}(\hat{p}_j|x,\delta)$ is increasing in $\hat{\sigma}_j$.[18]

The intuition for this is straightforward: the variance of $\hat{p}_j$ is equal to the variance in beliefs over rivals' average prices, multiplied by z_{pj}^2, which is already known. If j's signal were completely uninformative, j's beliefs would never change, and this variance would be zero. As the signal becomes more informative, it causes beliefs to vary more, and the variance in $\hat{p}_j$ increases. Call this, $\text{var}_{\hat{\sigma}_j}(\hat{p}_j|x,\delta)$, the "model-implied" variance.

At the same time, a higher guess of $\hat{\sigma}_j$ mechanically implies that the variance in $\hat{p}_j$ implied by the data must decrease. That is, if the conditional variance of p_j calculated directly from the data is

$$\widehat{\text{var}}(p_j|x,\delta) \equiv \int (p - \mathbb{E}(p_j|x,\delta))^2 \, dG(p_j|x,\delta),$$

then the guess of $\hat{\sigma}_j$ implies a "data-implied" variance of

$$\widehat{\text{var}}_{\hat{\sigma}_j}(\hat{p}_j|x,\delta) = \widehat{\text{var}}(p_j|x,\delta) - \hat{\sigma}_j^2.$$

This is obviously decreasing in $\hat{\sigma}_j$, because the first term on the right hand side can be caluclated from the data alone and is invariant to $\hat{\sigma}_j$. I now have the moment condition that the "model-implied" variance must match the "data-implied" variance:

[17] This is where assuming normality of ν_j is particularly useful: a deconvolution of a normal with variance $\hat{\sigma}^2$ can be attained from a sequence of deconvolutions of lower-variance normals with variances that sum to $\hat{\sigma}^2$.

[18] The definition of "responsiveness" in Vizcaíno & Mekonnen (2019) is, in general, more involved. However, all of the conditions implied by the definition of responsiveness are testable if we know the distribution of prices, suggesting that it is possible to relax the assumption that prices are affine in rivals' average price.

$$\mathrm{var}_{\hat{\sigma}_j}(\hat{p}_j|x,\delta) = \widehat{\mathrm{var}}_{\hat{\sigma}_j}(\hat{p}_j|x,\delta). \tag{7}$$

The left hand side of this equation is increasing in $\hat{\sigma}_j$, while the right hand side is decreasing in $\hat{\sigma}_j$. I can form a similar condition for each of the other firms, yielding J such conditions. Clearly, if each condition could be considered separately of the others (that is, the condition 7 did not depend on $\hat{\sigma}_{j'}$, for $j' \neq j$) the j-th condition would uniquely identify σ_j. However, the model-implied variance on the left hand side of equation 7 is also increasing in rivals' information quality. This is because, if $\hat{\sigma}_{j'}$ increases, for $j' \neq j$, then by the reasoning above, $\hat{\mathrm{var}}_{\hat{\sigma}_{j'}}(\hat{p}_{j'}|x,\delta)$ must increase. Because signals are positively correlated and the signal structure itself is common knowledge, this means that the variance of j's beliefs over the average of all rivals' prices must also increase, which finally implies that the variance of $\hat{p}_j$ must increase. Allowing all guesses of $\hat{\sigma}_{j'}$ for each firm $j' \in \mathcal{J}$ to vary, condition 7 can be written

$$\mathrm{var}_{\hat{\sigma}}(\hat{p}_j|x,\delta) = \widehat{\mathrm{var}}_{\hat{\sigma}_j}(\hat{p}_j|x,\delta)$$

where $\hat{\sigma} \equiv \{\hat{\sigma}_{j'}\}_{j' \in \mathcal{J}}$ is the entire vector of guesses for σ. In the appendix, I show that these conditions do yield a unique solution under my assumptions; that is, there exists a unique vector of $\{\hat{\sigma}_j\}_{j \in J}$ such that this condition is satisfied, for any dataset generated by this model. This is essentially a rank condition.

Given that I now know σ_j is, I can use equation 6 to construct the marginal distribution of the signal for each firm j, and the full, joint signal is constructed analogously, but using the joint (deconvolved) distribution of all prices, conditional on the demand shifters. All that remains is to identify $z_{\delta j}(.)$. This is done by matching model-predicted price distributions to the actual price distributions for different values of δ. Note that this step was impossible until the rest of the model was pinned down: otherwise, changes in prices arising from changes in δ_j may have either occurred because of $z_{\delta j}(.)$ or because δ_j is correlated with rivals' δ, and thus serves as a signal itself.

Reduced-Form Policy Function

A key feature of the above analysis is that I work directly with reduced-form pricing policy functions instead of writing down a structural model of marginal costs and conduct. Abstract, for the time being, from having incomplete information or any structural errors. Suppose I have estimated demand for hotel j on night t, and call this $Q_{jt}(p_{jt}, p_{-jt})$. The hotel's profit maximization problem would yield the following best-response:

$$p^*_{jt}(p_{-jt}) = \arg\max_p \quad pQ_{jt}(p, p_{-jt}) - C_j(Q_{jt}(p, p_{-jt})) \\ + \sum_{j' \neq j} \left[\theta_{j,j'}(Q_{j't}(p_{j'}, p, p_{-j't}) - C'_j(Q_{j't}(p_{j'}, p, p_{j't})))\right]$$

where $C_j(.)$ is the hotel's cost function and $\theta_{j,j'}$ are conduct parameters governing the degree to which j internalizes the profits of j'. With the correct variation in demand (e.g., the "shifts and rotations" in Bresnahan (1982) or Berry & Haile (2014)), the solution to this system of best-responses can be inverted to recover the supply primitives.

I do not take such an approach, because any structural supply specification I could write down in this spirit would almost certainly be misspecified. As mentioned before, hotel pricing is a complicated revenue management problem that is heavily studied in operations research and usually has no known analytic solution.[19] Hotels' revenue management practices are varied and their specifics are unknown. Any overarching revenue management objective function I impose would certainly be misspecified for some hotels; furthermore, because prices in my data are aggregated by night, I would have to impose strong assumptions, for instance, on the arrival process of travelers, in order to have an estimable revenue management-based model. Instead of explicitly writing down a structural model of the costs and considerations hotels face when choosing prices, I specify a reduced-form pricing rule that is (a) sufficiently flexible to fit the price outcomes of a complicated underlying problem and (b) sufficiently heterogeneous to account for differences across hotels in their practices.

When I do place more restrictions the policy function, they are drawn from Cho *et al.* (2018), who formulate a model of hotel revenue management that includes demand complementarities, responses to rivals' pricing, stochastic demand, and capacity constraints, and then estimate this model using extensive, detailed booking data from a hotel. They find that the reduced-form pricing policy involves undercutting rivals' average prices by some percentage if capacity is nonbinding and rapidly increasing prices if capacity is expected to bind. They obtain excellent model fit. My main pricing policy function specification, detailed in Section 4, involves a (1-z_p) fraction undercutting of rivals' average log prices and an exponential increase in prices as hotels' own demand increases.

[19] For a state-of-the art model of hotel revenue management, see Zhang & Weatherford (2016).

I now address three potential concerns with this approach. First, it does not yield structural estimates of costs. This makes it difficult, without further assumptions, to estimate variable profits to the extent marginal costs exist. However, marginal costs in the hotel industry are generally known to be small, as I discussed in Section 2; the most frequently-used industry benchmark of hotel performance is RevPAR, or "revenue per available room." So long as the supply specification yields credible predictions of prices and quantities, revenue and RevPAR are identified.

The second concern is that the policy function is not in any sense an optimality condition with regard to the other parameters of the model. That is, it does not directly assume expected revenue maximization by the hotels (though, as mentioned before, it is based on a revenue management model that approximates this). Though this is relatively unorthodox in industrial organization, I consider this a strength. In particular, in my counterfactuals, I do not implicitly assume that better information will yield higher revenues; the fact that revenues increase when I counterfactually improve information quality serves as both a quantification of the value of information that does not *assume* that information will be valuable, and a validation that the estimated policy function reflects, in some sense, franchisee efforts to maximize revenues.

The third criticism is that this approach does not fully model the firms' objective functions, so any counterfactual that changes the competitive environment (e.g., a merger), would be difficult to interpret. For this reason, I do not explore counterfactuals in this paper that change the overall competitive environment in a significant way. However, any counterfactual in which the competitive environment does change would still be valid so long as policy functions remain unchanged. This is an approach taken by Benkard *et al.* (2019),[20] who measure the long-run effects of entry in the airline industry using only the *reduced-form equilibrium distribution* of firms' actions given industry states. Their key assumption is that this mapping from states to distributions over action profiles is the same in their data as in their counterfactuals.

[20] Miller *et al.* (2019) also employ a reduced-form policy function approach in a similar spirit.

4 Empirical Specification and Estimation

Demand Specification

My main demand specification is a nested logit. A market t is defined as a city-night. I assume that there is no intertemporal substitution by consumers, so each market can be treated as separate in estimating demand. With few exceptions relating to entry and exit of hotels, market structure is constant over time, but because it varies across different cities, it varies with different t. Let $w(t)$ indicate whether city-night t is a weeknight (defined as Monday through Thursday nights). A hotel is indexed by j. The nest to which j belongs is $b(j) \in \{downscale, midscale, upscale\}$, and the set of hotels belonging to nest b in market t is $\mathcal{J}_{bt}$. Hotel j is also affiliated with brand $r(j)$. Let $J = 0$ represent the outside option, which is its own nest. Consumer i chooses among $J + 1$ total options. Utility is given by

$$\begin{aligned}
u_{ijt} &= -\alpha_{w(t)} p_{jt} + \lambda_{r(j),w(t)} + \beta \tilde{x}_t + \lambda_t + \xi_{jt} + \nu_{i,b(j),t}(\gamma) + \varepsilon_{ijt} \\
u_{i0t} &= \varepsilon_{i0t}.
\end{aligned}$$

p_{jt} is the hotel's price (average daily rate, in my data). $\tilde{x}_t$ includes a set of dummies for salient demand shifters; these are the shifters that I eventually assume are common knowledge. $\tilde{x}_t$ includes dummies for interactions between "high demand" status and city and interactions between day of week and city. $\lambda_{r(j)}$ is a fixed effect for the brand $r(j)$ associated with hotel j. λ_t is a city-night fixed effect that captures market wide demand shocks that are not related to salient features. These shocks are not considered common knowledge in my supply model. Finally, there is an unobserved hotel-night shock ξ_{jt}. ε_{ijt} and ε_{ij0t} are type-I extreme value draws that define consumers' idiosyncratic preferences for different hotels, and $\nu_{i,b(j),t}$ represents a nest-wide preference shock that scales with parameter $\gamma \in [0, 1]$. If $\gamma = 0$, ν is degenerate at zero, and demand is a standard multinomial logit. If $\gamma = 1$, products are perfect substitutes within-nest.

I allow $\alpha_{w(t)}$, which measures price sensitivity, to be different on weeknights versus weekends. That is, the latent utility of price is different on weeknights versus weekend. This is a simple way to capture heterogeneity in tastes between business travelers and leisure travellers, as well as between travellers. This may, in turn, be associated with changes to hotels' supply strategies depending on whether the night is a weekend. Accordingly, in my supply specification later on, I allow the supply model— specifically, the parameters of hotels' price policy functions and their information quality— to be different on weekends versus weekdays. Alternative demand models may include a random coefficient on price (i.e., a mixed logit) or explicitly model discrete consumer types, their tastes, and their proportions (see, e.g. Berry & Jia (2010)). I use this as my main specification because it parsimoniously captures the most essential parts of demand for my analysis: (1) the variation in travel demand over time and (2) the intensity of competition within-nest versus across nests. The former is the object about which hotels gather information and a main source of supply-side identification; the latter is the basis for my supply model, specifically the aggregative-within nest structure of price policy functions.

This specification yields predicted shares

$$s_{jt} = \frac{\exp(\bar{u}_{jt}/\gamma)}{\sum_{j' \in \mathcal{J}_{bt}} \exp(\bar{u}_{j',t}/\gamma)} \frac{\exp(V_{b(j)t})}{1 + \sum_b V_{bt}}. \tag{8}$$

$\bar{u}_{jt} \equiv -\alpha_{w(t)} p_{jt} + \lambda_t + \beta \tilde{x}_t + \lambda_j + \xi_{jt}$ is the mean utility of option jt, and V_{bt} is the logit inclusive value of nest b. This equation can be re-expressed as

$$\log(s_{jt}) - \log(s_{0t}) = -\alpha_t p_{jt} + \lambda_{r(j)} + \beta \tilde{x}_t + \lambda_t + \xi_{jt} + \gamma \log(s_{jt|b(j)})$$

where $s_{jt|b(j)}$ is j's share of all bookings in nest $b(j)$. This expression makes clear that a key threat to identification of this model is the endogeneity of prices. In particular, suppose a hotel receives a demand shock ξ_{jt} and increases its prices accordingly. This will lead to positive correlation between prices and number of rooms booked. Because a unit of observation in my data is jt-specific, I cannot simply condition on unobserved ξ_{jt}. As is standard in demand estimation, I solve the endogeneity of prices by using instruments that shift prices and shares but are not part of the product's demand. These instruments also serve to identify the nesting parameter γ.

Valid instruments W must affect firm prices and shares while also satisfying the exclusion restriction

$$\mathbb{E}(W\xi | \lambda_{r(j)}, \lambda_t, \tilde{x}_t) = 0$$

The most obvious candidates for instruments in such models are marginal cost shifters. However, marginal cost shifters are uncommon in the hotel industry; in part because there are hardly any marginal costs at all. Cho *et al.* (2019), for instance, cite lack of cost shifters as a reason they rely on supply-side restrictions in order to identify hotel demand without using instruments at all.

Unlike in Cho *et al.* (2019), my data contain variation in market structure across geographic markets. This allows me to use variation in rival characteristics as instruments that shift markups and shares, in the spirit of Berry *et al.* (1995). These are selected based on the characteristics of my supply model: my hypothesis is that larger parent companies price differently than small parent companies, due to differences in information quality, and that pricing strategy depends on the ownership and chain affiliation of the hotel as well as of its rivals. As a result, number of within-nest rival rooms, the number of within-nest rival rooms at hotels affiliated with the same parent company, and the interaction of all of these terms with two market-wide exogenous demand shifters: a dummy for whether it is a weekend and a dummy for whether it is a high-demand day.

Supply Specification

The previous identification strategy shows that parts of the model can, in theory, be recovered nonparametrically. However, because nonparametric estimation can behave poorly in finite samples, I impose more parametric restrictions on the model that I estimate. Fix a geographic market and a particular market segment. That is, hotels set prices in response to other firms in the same city and the same segment; this corresponds to the "comp set" hotels use as a benchmark through the Star Reports alluded to in section 2. Now, t indexes time only. Firms choose log-prices according to a fully linear strategy:

$$\log(p_{jt}) = z_{0j} + z_{pj}\mathbb{E}(\log(\bar{p}_{-jt})|s_{jt}, \delta_{jt}, x_t) + z_{\delta j}\delta_{jt} + \nu_{jt}.$$

where $\delta_{jt} = \lambda_{r(j)} + \beta\tilde{x}_t + \lambda_t + \xi_{jt}$, i.e., it is the mean utility (net of price) from the demand system. For simplicity, from here forward, I write $x_t \equiv \beta\tilde{x}_t$ and treat x_t as a demand shifter. I also assume the intertemporally-varying demand shifters, λ_t, x_t and ξ_{jt} are jointly normal. Each firm's signal is the unknown market shifter, λ_t, plus error:

$$s_{jt} = \lambda_t + \rho_j\sigma_{\lambda,m}\zeta_{jt}$$

where ζ_{jt} is a standard normal random variable. Here, $\sigma_{\lambda,m}$ is the standard deviation of λ over time in city m, and ρ_j scales the amount of noise in j's signal. The smaller ρ_j, the better informed the hotel. Note that, in this specification, I have ruled out signals that are correlated among hotels, conditional on λ.[21]

This specification has the appealing property that prices are ultimately linear in the variables that the hotel observes. Specifically, for hotel j,

$$p_{jt} = \hat{z}_{0j} + \hat{z}_{sj}s_{jt} + \hat{z}_{\delta j}\delta_{jt} + \hat{z}_{xj}x_{jt} + \nu_{jt} \tag{9}$$

where $\hat{z}$ are reduced-form coefficients that arise from the model. I go through the steps involved to obtain this form from the primitives of the model in appendix B.

Estimation

Estimation proceeds in two steps. I first estimate a set of the *reduced-form* coefficients that are the empirical analogue of $\hat{\mathbf{z}}$. Then I obtain the model parameters $\{z_{pj}, z_{\delta j}, z_{0j}, \sigma_j\}_{j\in J}\}_{j\in J}$ by matching the estimated reduced form parameters to the reduced form $\hat{\mathbf{z}}$ that arises from the model. That is, I obtain $\hat{z}$ using the steps outlined in appendix B and match them to reduced-form coefficients.

To obtain the reduced-form parameters, I first note that, adding the errors back to equation 9, the reduced form of the model is

$$\begin{aligned}
p_{jt} &= \hat{z}_{0j} + \hat{z}_{sj}s_{jt} + \hat{z}_{\delta j}\delta_{jt} + \hat{z}_{xj}x_t + \nu_{jt} \\
&= \hat{z}_{0j} + \hat{z}_{sj}[\lambda_t + \rho_j\sigma_{\lambda,m}\zeta_{jt}] + \hat{z}_{\delta j}\delta_{jt} + \hat{z}_{xj}x_t + \nu_{jt} \\
&\equiv \hat{z}_{0j} + \hat{z}_{sj}\lambda_t + \hat{z}_{\delta j}\delta_{jt} + \hat{z}_{xj}x_t + \hat{\nu}_{jt}
\end{aligned}$$

where $\hat{\nu}_{jt}$ contains both the noise coming from the signal and the noise coming from the structural error. I obtain consistent estimators of the reduced form parameters $\hat{\mathbf{z}}$ using feasible GLS. For a guess of model parameters, I then solve the model to obtain $\hat{\mathbf{z}}$. I then search over

[21] A slightly more general model allows different degrees of correlation in signals depending on whether hotels belong to the same parent company:

$$s_{jt} = \lambda_t + \rho_j\sigma_{\lambda,m}[\theta\zeta_{h(j),t} + (1-\theta)\zeta_{j,t}]$$

where $\zeta_{h(j),t}$ is a normal draw that is common all hotels in j's parent, $h(j)$. I set $\theta = 0$ in my main specification due to limited data. Due to data limitations, estimates of a richer model in which I also estimate θ using additional moments from the variance-covariance matrix in pricing errors, were poorly behaved. With more data, I hope to obtain estimates of this richer model.

parameters to minimize the distance between $\hat{z}$ and the reduced-form coefficients from GLS.[22] This yields my estimates of the underlying parameters.

Although I will not rehash the detailed identification arguments in section 3, it is worth noting how these reduced-form coefficients intuitively map to primitives in this model. Because x_t is common to all hotels, while δ_{jt} is not, difference between $\hat{z}_{jt}$ and $\hat{z}_{xt}$ measures the degree of complementarity between hotels, as in z_{pj}. The difference between $\hat{z}_{sj}$ and $\hat{z}_{xj}$, as in the previous discussion, then identifies information quality ρ_j. $\hat{z}_{0j}$ and $\hat{z}_{\delta j}$ then identify c_j and $z_{\delta j}$, respectively, and the remaining noise in $\hat{\nu}_t$, after accounting for ρ_j, identifies σ_j.

5 Estimates

Demand parameter estimates from the nested logit are reported in Table 4. As expected, consumers booking more upscale hotels are less price sensitive. Because there is a city-night fixed effect, different specifications of market size do not affect estimates of any parameters other than the fixed effects. Table 5 shows summary statistics of estimated own-price elasticities. These are roughly in line with other recent hotel demand estimates in the literature, e.g., Farronato & Fradkin (2018).

Table 4: Demand estimates

Demand variable	Estimated coefficient (Std. Error)
ADR/100	-1.560
	(0.056)
ADR*1[Weekday]/100	-0.384
	(0.107)
Nesting Parameter, γ	0.240
	(0.010)

Notes: Data from STR, Inc. Estimates from nested logit. Market is a city-night; downscale hotels classified based on STR classification. GMM standard errors reported.

In Figure 5 I plot kernel densities of the observed and unobserved components of market demand for weekends and weekdays, respectively. The amount of variation unobserved and observed demand shocks is similar; variation in the observed shock x_t is slightly larger overall,

[22] Of course, OLS also yields consistent estimates; because the model clearly predicts that errors will be correlated amongst hotels, and I use the standard errors of the estimated $\hat{z}$ to construct the weighting matrix for my criterion (see appendix equation A.12), I use two-step GLS.

Table 5: Elasticity estimates, by segment

		Cross-Price Elasticities	
Segment	Own-	Within-Nest	Without-Nest
Downscale, Weekday	−1.586	0.040	0.018
Downscale, Weekend	−1.543	0.046	0.023
Midscale, Weekday	−2.642	0.078	0.032
Midscale, Weekend	−2.396	0.084	0.037
Upscale, Weekday	−3.165	0.368	0.036
Upscale, Weekend	−2.917	0.377	0.043

Data source: STR, Inc. Own-price elasticities calculated using point estimates from nested logit at observed prices and shares, for each hotel-night in dataset. Mean and median are calculated for each bin.

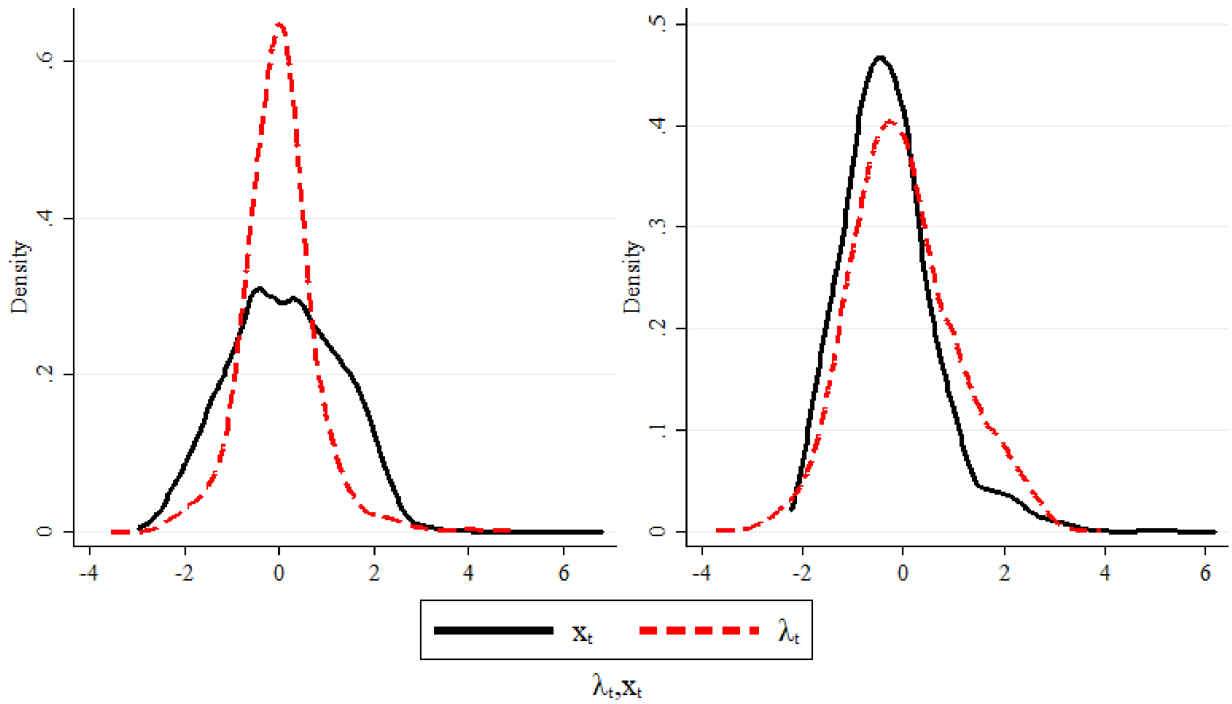
but some of this is driven by cross-city variation. These distributions are also approximately normal, consistent with my distributional assumptions.

I then estimate supply parameters according to the procedure described in the previous section for each of seventy-two submarkets: eighteen geographic markets, times two day of week categories $\{weekend, weekday\}$, times two quality segments $\{downscale, midscale\}$. I estimate weekends and weekdays separately because demand shifts on weekdays are not directly comparable to demand shifts on weekends. Because consumers are estimated to be more price sensitive on weekdays than on weekends, a demand shift of size Δx_t corresponds to a smaller money metric change in latent utility on weekdays than on weekends. Estimating weekend supply separately from weekday means that I do not get to use the difference between weekends and weekdays—a natural, fairly predictable demand shift that could be assumed to be common knowledge—as identifying variation. Instead, the common-knowledge shifters are day-of-week (e.g., Saturday versus Sunday for weekends) and the "high demand day" indicator, interacted with city.[23] Because upscale hotels draw significant revenue through channels other than booking rooms, I do not estimate supply for the few upscale hotels in my dataset. The supply parameter estimates are summarized in Table 6.

[23] I am intentionally conservative in the number of variables I allow to be common-knowledge shifters. This is because the identification strategy requires the common-knowledge shifter to absolutely be common knowledge; the remaining demand variation is allowed to have some common knowledge components, so even if I err on the side of classifying too much demand variation as imperfectly known, my results are still valid.

Figure 5: Kernel density plots of market demand shifters

(a) Weekdays (b) Weekends



Data source: STR, Inc.

Model Fit

I present summaries of model fit in Figure 6. Overall, the model does a good job of matching the unconditional price densities in the actual data, especially given how parsimonious the supply specification was. In particular, I am able to match the right tail of prices in the data by allowing firms to choose log-prices and price levels. Occupancy model fit is slightly worse; I over-predict sellouts and under-predict near-sellouts. This is likely because hotels are not necessarily single-product firms: if a hotel is at 95% occupancy, but all of the remaining rooms have single beds, this hotel is essentially sold out to a traveller who desires two beds in a room. My model generally predicts revenues per available room (RevPAR) well, though it slightly under-predicts RevPAR overall.

The heatmaps in the second row of Figure 6 show that my fit is generally good at the hotel-night level. These heat maps plot the joint density of actual versus model-predicted price, occupancy, and RevPAR for each hotel-night in my data. There is relatively little spread

Table 6: Supply estimates

	Percentile		
	25th	50th	75th
Information quality:			
Information parameter, ρ	0.694	2.021	5.028
Signal-to-noise ratio $\frac{1}{1+\rho}$	0.166	0.331	0.590
Shannon information, $Shannon(\rho)$	0.019	0.109	0.562
Policy functions:			
Price coefficient, z_p	0.054	0.474	0.916
Idiosyncratic noise, σ	0.000	0.065	0.086
Delta coefficient, z_δ	0.000	0.083	0.256
Revenue gains from full information:	Mean	Std. Dev.	
all firms	3.50%	3.81%	
cond. on $\rho >= \bar{\rho}$	4.71%	4.51%	

Data source: STR, Inc. A different estimate of each parameter is calculated for each hotel-1[weekday]. Percentiles, mean and standard deviation are taken across all of these estimates. Shannon information calculated according to Equation 10. Revenue gains from full information calculated by simulating revenues for each hotel j if $\rho_{jw} = 0,\ w = 0, 1$ and are reported as percentage increases in revenue. See Appendix C for simulation details.

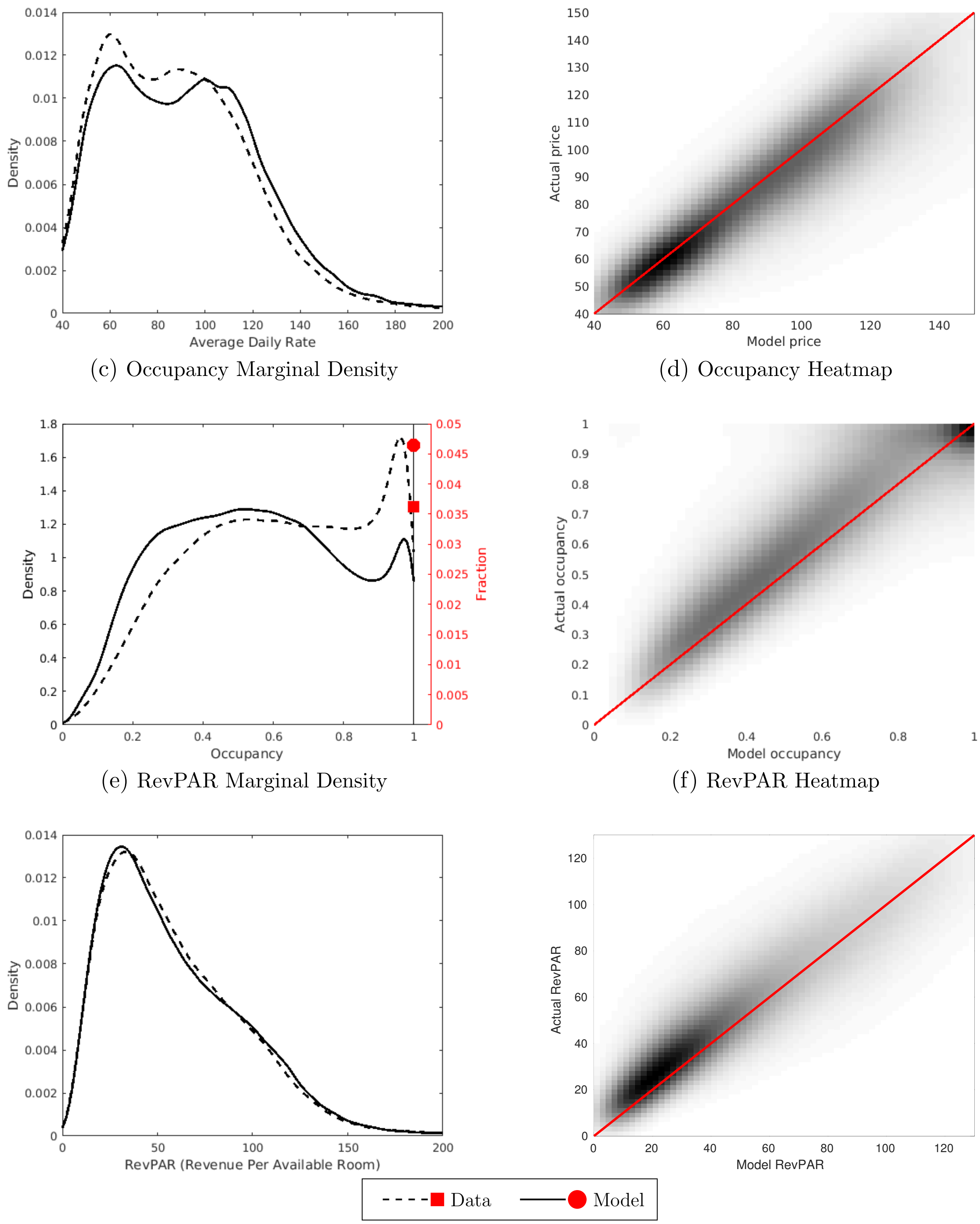
around the 45-degree line, suggesting that, even disaggregated to the hotel-night level, my model predicts these outcomes fairly well. Over 80% of simulated prices are within $\pm 10\%$ of the actual prices. This amount of error is consistent with the amount of noise I estimated (e.g., the median across j of σ_j is .065, corresponding to prices fluctuating by about 6.5% from expected, on average).

Heterogeneity in Information Quality

As reported in Table 6, there is clearly a significant amount of heterogeneity in information quality across hotels. Note that $\frac{1}{1+\rho}$ is, by construction, between 0 and 1, with a value of 0 corresponding to no information and a value of 1 corresponding to perfect information.

Furthermore, imperfect information has significant consequences for the hotels in my data. Specifically, increasing information quality can lead to significantly higher revenues, especially for the hotels that are poorly informed. I obtain estimates of the gains from information as follows: using the policy function estimates I obtained, I simulate prices and occupancy for for each day in my dataset. I then run the same simulation, but with $\rho_j = 0$; note that, because hotels interact with one another in my model, this may change rival hotels' pricing as well. I use simulated prices and occupancies to generate expected annual revenues for j.

Figure 6: Model fit



(a) Price Marginal Density

(b) Price Heatmap

(c) Occupancy Marginal Density

(d) Occupancy Heatmap

(e) RevPAR Marginal Density

(f) RevPAR Heatmap

Data source: STR, Inc.

The details of the simulation procedure are in C. I do this for each hotel in my data; these results are summarized in the bottom half of Table 6. Moving to full information leads to nontrivial gains in revenue on average; notably, because the price policy function in my model is not a first order condition of revenues with respect to prices, this is not by construction. Instead, it indicates that hotel managers could benefit from pricing differently— specifically, by responding to unknown demand shocks as much as they do to common-knowledge shocks— but they lack the capability to do so. Not surprisingly, the gains from perfect information are larger for poorly-informed hotels (i.e., those with ρ_j greater than the average across all hotels, $\bar{\rho}$, as reported in the bottom row of Table 6).

I then examine whether affiliation with "industry leader"— large upscale— chains is associated with better information. I transform the estimated ρ_{jw} into Shannon mutual information, a commonly-used measure of signal quality, on market fixed effects and fixed effects for affiliation with the five largest parent companies (the excluded category includes independent hotels and hotels that are affiliated with smaller chains). Shannon information is calculated as

$$Shannon(\rho_{jw}) = \log\left(\frac{\sqrt{1+\rho_{jw}^2}}{\rho_{jw}}\right). \tag{10}$$

I estimate the following equation:

$$Shannon(\rho_{jw}) = a_{parent\ type} + a_m + u_{jw}. \tag{11}$$

This measures the correlation between information quality and parent company affiliation, conditional on the market that hotel is in. The parent company fixed effects, and their standard errors,[24] are reported in Table 7. The upscale large parent companies, typically considered the most sophisticated, are actually the worst-informed.

In order to differentiate between the effects of analytic sophistication— which likely varies across chains and may or may not be correlated with size— and quantity of data— which is mechanically correlated with size— on hotel information quality, I leverage variation in market structure across different cities. In particular, some parent companies have a larger presence in some cities than in others, which allows me to separately estimate the effect of parent

[24]These standard errors are based only on the OLS regression of information quality on the fixed effects. They do not reflect that information quality is itself estimated. These standard errors are clustered at the market level.

company identity, which may include some measure of that parent company's sophistication, and parent company share, which is a direct measure of the parent company's size in a given market. I do this by including another regressor in the second specification of Table 7. This regressor, $ParentShare_j$ measures the percentage of rooms j's market affiliated with the same parent company as j. The coefficient on this regressor is very close to zero, suggesting that chain size alone does not improve information quality. This runs against the hypothesis that a larger presence in a particular market allows the parent company to collect more data and make better inferences about demand.

Table 7: Information quality, by parent type

Dep. Var	Shannon	Shannon
1[Downscale Big]	0.139	0.134
	(0.178)	(0.275)
1[Upscale Big]	-0.378^{*}	-0.382
	(0.196)	(0.264)
Parent Share	-	0.037
		(1.690)
Omitted Parent Type	Small	Small
Market FE	Y	Y
Observations	1,444	1,444

Data source: STR, Inc. Regression of estimated Shannon information quality on parent company type and market (i.e., city) fixed effects. An observation in this regression is a hotel-1[Weekday]. Standard errors are clustered by city-class-1[weekday] but do not reflect that information quality is itself estimated.

Taken together, these results suggest that there are not informational advantages to scale in the hotel industry, regardless of whether the source of advantage is analytic sophistication that can only be afforded by larger companies, or the mechanical effect of larger scale, e.g., through generating more data for the parent company about a particular market. In fact, the large upscale chains—the largest parent companies in terms of, for instance, national booking revenues—are systematically worse informed in these markets. I now present evidence that this gap may be explained by differences in franchisee information-gathering incentives. In particular, the parent companies with the worst information quality, according to my estimates, also charge the highest royalties to their franchisees, and this induces differences in franchisee information-gathering incentives.

Alternative Hypotheses of Information Gathering

First, however, I address a number of alternative hypotheses. First, a number of hypotheses, which I will collectively call brand effects, suggests that large-chain hotels may appear to be worse-informed because of some other reason. For instance, prices at larger chains may be noisier because of a preponderance of discounts, loyalty bookings, package deals, and so on. This set of hypotheses can immediately be ruled out based on the model and methodology I applied. The model explictly accounts for two separate sources of noise: that generated by uncertainty over demand, and noise that directly enters the pricing policy rule. The methodology uses the common knowledge shifters as a way to disentangle these two sources of noise. This underscores the importance of my methodological innovation: without a common-knowledge shifter, I would not have been able to discriminate between information quality and noisy pricing.

A second hypothesis relates to group and corporate bookings. The non-common knowledge market demand variation in my model, λ_t, measures all market-wide increases in occupancy (conditional on prices) that are not explained by day-of-week or a flagged high-demand day. Some of these shifts may be market-wide shifts related to the university that I do not flag, such as large conferences. This would imply that a high realization of λ_t may be associated with a large number of group bookings through the university. If upscale large chains offer deeper discounts for group bookings than small chains, this may flatten the price response of upscale large chains to changes in λ_t, which I would infer as poor information. To address this, I measure how informational differences between upscale large chains and small chains varies with the probability that λ_t comes from a large university-wide event, by using measure of how important the university is to that particular city m. This measure is university enrollment per hotel room:

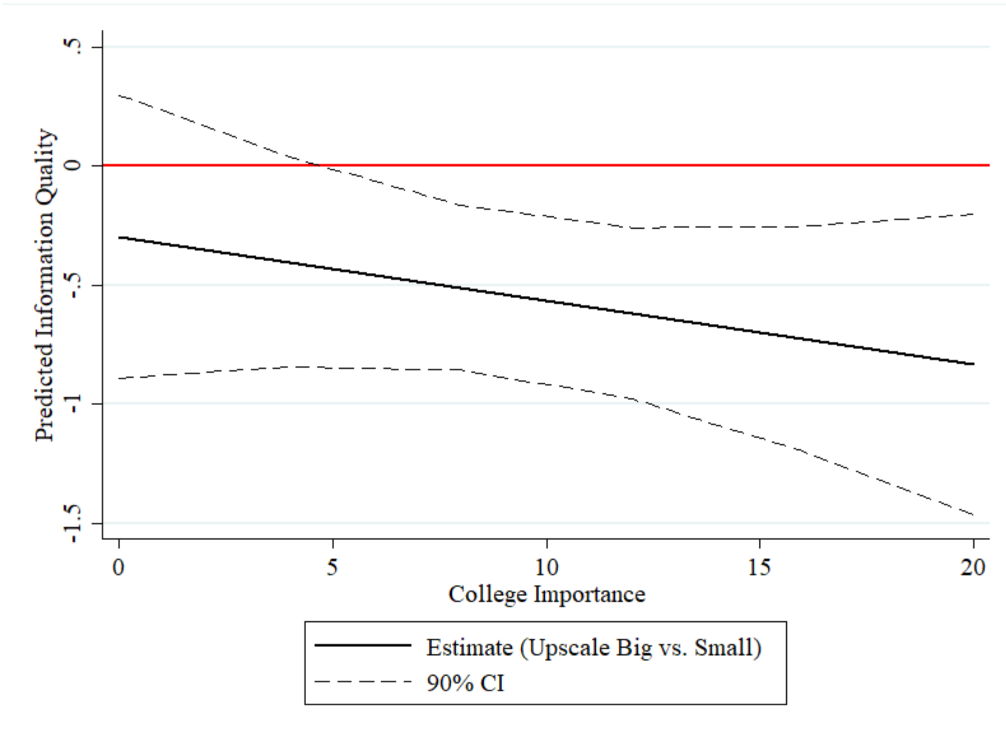
$$Importance_m = \frac{Enrollment_m}{\sum_{j \in \mathcal{J}_m} Capacity_j}.$$

I then perform the following regression:

$$Shannon(\rho_{jw}) = a_{parent\ type} + \beta Importance_m + \sum_y \mathbf{1}[Parent\ Type = y] * Importance_m.$$

If this hypothesis were true, we would see a sizable difference in estimated information quality between small and upscale large parent companies only for markets in which the university is especially important. I plot the predicted difference in information quality between upscale large parent companies and small parent companies as a function of university importance in Figure 7.

Figure 7: Information quality differences versus university importance

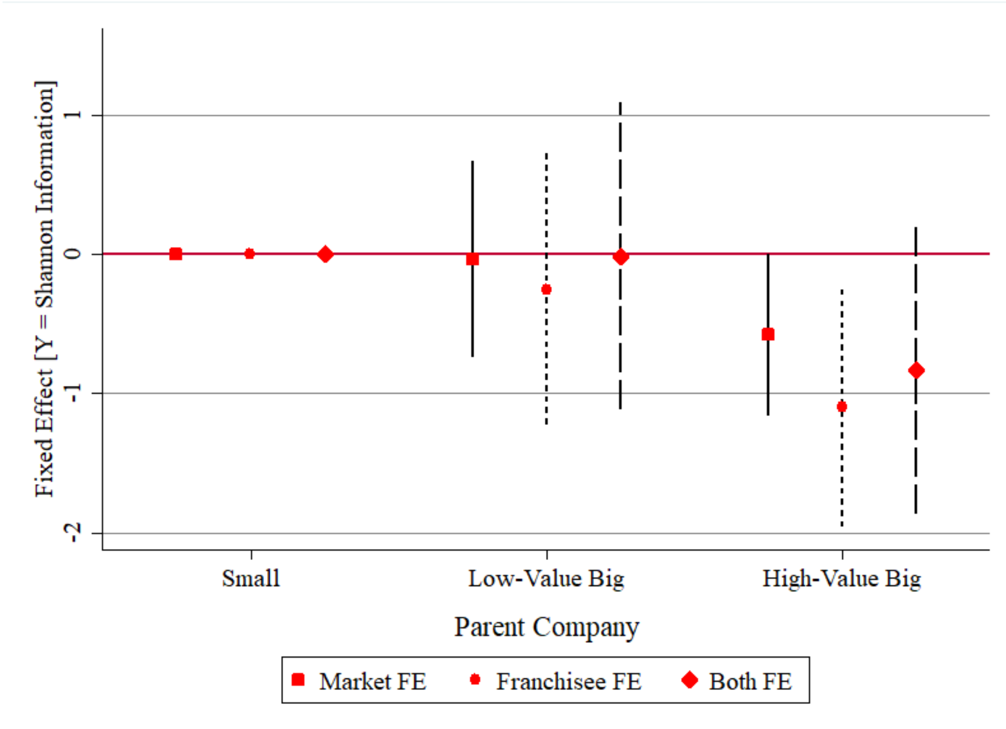


Data source: STR, Inc.

I find the opposite: the gap between predicted information quality between small parent companies and upscale large parent companies is largest for markets in which the university is especially important according to my measure.

The third hypothesis is about franchisee sorting. According to this hypothesis, higher-ability hotel managers (i.e., those who are better equipped to monitor and respond to demand fluctuations) are systematically more likely to affiliate with smaller chains or operate independent hotels. If the franchisee sorting hypothesis were true, differences across chains would vanish once I condition on a franchisee fixed effect. That is, a small-chain hotel and a large-chain hotel should have the same amount of information if they are owned by the same franchisee. On the other hand, if the franchisee effort hypothesis were true, this may not always be the case. If a franchisee owns a small-chain hotel and a large-chain hotel, and, in accordance

Figure 8: Heterogeneity in information by parent type for multi-hotel franchisees



Data source: STR, Inc.

with this hypothesis, only provides effort into managing demand at the small-chain hotel, the large-chain hotel may indeed remain less-informed. This would certaintly be true if the two hotels operated in different markets, where knowing demand at one hotel is unhelpful at the other hotel. It may still be true if the hotels were in the same market, to the extent that information is not perfectly transferable between hotels, but possibly quite diminished.

Figure 8 provides evidence against the franchisee sorting hypothesis and in favor of the franchisee effort hypothesis. It reports the fixed effects from three different specifications, all of which explain variation in Shannon information across hotels owned by multi-property franchisees. That is, I restrict my sample only to hotels whose franchisee also owns other hotels in my dataset. First, I repeat regression 11 but instead just this subset of hotels. The estimates for this subset are largely similar to the regressions on the entire set of hotels. The second specification replaces the market fixed effect in this regression with a franchisee fixed effect. That is, it compares two hotels owned by the same franchisee, though these hotels may be in different markets. The point estimate actually *increases* in magnitude, suggesting that differences in information quality between a large-chain hotel and a small-chain hotel, conditional on franchisee, may in fact be larger than my main specification suggests. Put another way, franchisee sorting may run the opposite direction of the hypotheses: high-ability franchisees are *more* likely to work with large chains, which would be unsurprising given the large capital and financing requirements associated with franchising from large brands.

The third specification in this figure contains both market and franchisee fixed effects. Because there are not many hotels in this restricted subset, adding both layers of fixed effects returns very noisy estimates. However, the point estimate of the difference between large- and small-chain hotel information quality becomes smaller in magnitude, suggesting that, consistent with the franchisee effort hypothesis, there may informational spillovers from the franchisee's small-chain hotel to the same franchisee's large-chain hotel.

Franchisee Effort and Information-Gathering Incentives

In table 8, I provide evidence that these differences in effort level could be explained by differences in marginal royalty rates. The large upscale chains tend to charge higher royalties on revenues, which may induce franchisees to gather less of information needed to optimize revenues. In the first column of this table, I again report the results of the baseline specification 11, limited to hotels that were successfully matched to marginal royalty rates. In the second column, I replace λ_{parent} with the marginal royalty rate. The coefficient suggests that an increase in the marginal royalty of 4%, roughly the average difference between small-chain and upscale large-chain hotels, would cause Shannon information to decrease by .08. Given that the variance, across hotels, in Shannon information is over 2, this seems like a small change. However, as I show in the next subsection, differences in royalties are enough to explain differences in information quality between large and small chains.

These results become markedly more pronounced when I limit this analysis to hotels owned by multi-unit franchisees. These franchisees are presumably better-informed about differences between parent companies in regards to their contractual terms, pricing practices, and support for franchisees. These differences may also come from limited managerial attention: franchisees with multiple properties, having to devote some amount of effort in managing revenue at a number of locations, are forced to allocate most of their information-gathering efforts to the hotels where returns are greatest.

As a final exercise, I examine what may happen if we were to eliminate differences in moral hazard across hotels. In order to see, this, consider the following, highly stylized model. A franchisee chooses information quality $\frac{1}{1+\rho}$ in order to maximize profits at hotel j:

Table 8: Information and royalty fees

	All Matched Hotels		Multi-Hotel Franchisees	
Specification	Baseline	Royalties	Market FE	Franchisee FE
Dep. Var.	Shannon	Shannon	Shannon	Shannon
1[Downscale Big]	0.258	-	-	-
	(0.233)			
1[Upscale Big]	-0.461^{*}	-	-	-
	(0.258)			
Marginal Royalty	-	-2.014	-12.763^{*}	-12.831
		(2.246)	(6.702)	(8.221)
Constant	0.849^{***}	0.910^{**}	2.319^{**}	3.663^{*}
	(0.304)	(0.353)	(0.956)	(1.931)
Observations	1,370	1,370	275	275
R-squared	0.108	0.095	0.121	0.211

Data source: STR, Inc. and HVS. An observation is a hotel*1[weekday]. Standard errors are clustered by city-class-1[weekday] but do not reflect that information is itself estimated. Omitted category of parent company in first column regression is small chains and independents. All regressions include a city-level fixed effect.

$$\max_{\rho_j} \mathbb{E}\Big(\sum_t (1-\gamma_j) R_{jt}(\rho_j)\Big) - c\Big(\frac{1}{1+\rho_j}\Big) - F_j$$

where F_j is the operating cost of the hotel, γ_j is the royalty rate on booking revenues, and $R_t(.)$ is the hotel's revenue on night t, and $c(.)$ is a convex, increasing effort cost of acquiring information. I assume that $c(.)$ does not vary by hotel or franchisee (consistent with there being no sorting of franchisees according to ability by chain). The first order condition is

$$(1-\gamma_j)\sum_t \frac{\partial \mathbb{E}[R_{jt}(\rho_j)]}{\partial \rho_j} = c'\Big(\frac{1}{1+\rho_j}\Big).$$

Given that the effort cost function does not vary by hotel, if I can estimate the right hand side of this equation for each hotel, I can estimate the cost function. I estimate the right hand side by taking a linear approximation. Suppose I have estimated information quality at hotel j to be ρ_j. I simulate annual revenues $\hat{R}_j$ for hotel j if its information quality were $\rho_j + \Delta$ and if its information quality were $\rho_j - \Delta$. I then calculate $\frac{\hat{R}_j(\rho_j+\Delta)-\hat{R}_j(\rho_j-\Delta)}{2\Delta}$. Call this $\widehat{MR}_j$. In Appendix D, Figure A.2, I show that, on average, revenues are approximately linear in information quality. I then fit the regression

$$(1-\gamma_j)\widehat{MR}_{jw} = c_m + c_{parent} + c_2 \frac{1}{1+\rho_j} + u_j \tag{12}$$

where c_m is a market fixed effect to account for the possibility that information is more difficult to obtain in some markets than others (for instance, some markets are inherently more unpredictable), and c_{parent} is a fixed effect for each of six different parent company categories (the five large parent companies and small chains/independents). These estimates provide an estimate of the marginal cost of effort.[25]

I report detailed estimates of this cost-of-information gathering-effort regression in Appendix D. The mean estimated annual cost of moving from no information to full information is \$83,298. For comparison, leading third-party revenue management platforms such as Duetto and IDeaS, charge annual fees of roughly \$12,000 to provide services to a 100-room hotel. This implies that on average, a 100-room hotel would be indifferent between subscribing to such a platform and gathering the information itself if the platform improved the hotel's information quality from the median to roughly the 70th percentile. This is roughly the same gain I predict an upscale large-chain hotel with the median information quality would attain if it switched to being a small chain. This means that the difference between a small-chain's information quality and a large-chain's information quality corresponds to the average willingness to pay for a subscription to a third-party revenue management service.

Once I have these cost estimates, I predict effort levels for each hotel if $\gamma_j = .11,\ \forall j$. This is approximately the median royalty fee across all hotels. I replace the left hand side of equation 12 with $(1-.11)\widehat{MR}_j$, and then solve this equation to obtain a new effort level; call this $\hat{\rho}_j$. Finally, I repeat regression 11 using $\hat{\rho}_j$ instead of the estimated ρ_j. The results of this regression are reported in column 2 of Table 9 alongside the original regression results. Not surprisingly, because royalty fees are higher at the large-chain brands in general, the difference in information quality between large- and small-chain brands shrinks. However, the size of the effect of changing royalties is surprisingly large. In this stylized counterfactual, large chain hotels (both upscale and downscale) are better-informed than small-chain and independent hotels, consistent with the more commonly-held theory that size yields an informational advantage. Overall, my findings suggest that there may indeed be informational advantages of size, but they are dwarfed by the effects of managerial incentives.

Furthermore, this exercise suggests that differences across royalty fees, though not exactly

[25]Because I am assuming a first order condition must hold, I only do this using hotels with interior solutions; that is, I do not include hotels with near-perfect or near-zero information in this regression.

Table 9: Same royalty fees counterfactual

	Baseline	Royalties=11%
Dep. Var.	Shannon	Shannon
1[Downscale Big]	0.139	0.434*
	(0.178)	(0.172)
1[Upscale Big]	−0.378**	0.319
	(0.170)	(0.302)
Constant	0.983***	2.248***
	(0.282)	(0.396)
Observations	1,444	1,444
R-squared	0.107	0.053

Data source: STR Inc. Regressions of Shannon information and counterfactual Shannon information on market fixed effects and parent type fixed effects. Shannon information caluclated from estimates and counterfactual estimates of ρ according to Equation 10. An observation is a hotel-1[Weekday]. Standard errors are clustered at the market-class-1[weekday] level, because supply was estimated separately for each market-class-1[weekday], but the standard errors otherwise assume all variables in the regression estimated without error.

large in percentages, are large enough to make significant impacts on franchisee effort. This heterogeneity is most often thought of as being driven by differences in brand quality: if you want to carry a high-quality brand, you must pay a higher royalty; this royalty essentially serves as a markup on the brand. But this markup comes at a cost: because franchisee effort depends on royalties, high-quality brands are less keenly managed than small chains and independent hotels. In fact, it seems that there are two different business models at play: an "upscale model" in which the chain invests in brand quality, charges a higher markup on this quality, and franchisees rely on this brand quality in lieu of more acute pricing strategies; and a "downscale model" in which the chain does not invest much in its brands, but relies on its franchisees to manage demand effectively, and provides higher-powered incentives in order to ensure this. In appendix figure A.3 I outline the tradeoffs in terms of expected annual revenues for a franchisee who is choosing between the upscale model and the downscale model. The upscale model yields higher expected annual revenues, net of royalty fees and information-gathering costs; the analysis does not include other considerations, such as fixed and operating costs, which are likely higher at upscale large chains.

6 Conclusion

We know little about what features of the firm determine the quality of its information about the market. This paper shows that, in the hotel industry, incentives dominate scale. Managerial effort, rather than big data, is the key driver of hotel information quality, even though parent companies regularly send informative price recommendations to franchisees from their analytics offices. My interpretation of this finding is that "local knowledge" is especially important in this industry. As a result, managers are best positioned to gather this information, rather than corporate headquarters, so their incentives to gather information play a key role in the hotel's information quality.

In order to answer this question, I have provided useful answers to some intermediate questions. I developed a novel methodology to identify agents' information quality when this information is about a common state variable. This methodology can be applied, with minimal adjustments, to other settings where the analyst observes the unknown state *ex post* and can assume that some component of this state is common knowledge to the agents. Methodologically, there is still room to estimate a more general model as alluded to in footnote 16. The most natural extension in this regard would be to incorporate unobserved heterogeneity at the market level; that is, to complement pricing error ν_{jt} with a market-wide error ν_t.

Further work, especially in management and strategy, could examine the ultimate effects of different levels of brand quality investment, coupled with alternative franchisee contract terms, on hotel performance. This paper suggests that there is a need in the literature at large to examine the effects of managerial incentives on information-gathering and firm performance, hand-in-hand with existing analyses of how brand value and quality investment drive firm performance. A natural extension of this paper is to use the estimates of this model to find the "optimal" contractual terms between parent company and franchisee. Though other considerations, such as fixed costs and entry conditions, are probably needed to conduct such an analysis, this paper presents evidence that royalty rates and franchisee incentives to gather information and price effectively are first-order.

Finally, this paper emphasizes that no sweeping conclusions should be drawn about firm size and information quality. Other industries where demand uncertainty figures prominently in pricinc, such as the airlines industry, are vertically integrated (albeit not fully integrated for all routes; see Forbes & Lederman (2009)) and more concentrated. This paper sheds light on why these industries are organized so differently: in the airline industry, local information is relatively less important, and the network structure of flights requires a significant degree of coordination. This implies that decisions should be made by a centralized, upstream body, that there are likely gains to scale and scope, The findings of this paper may not be entirely specific to the hotel industry: downstream incentives are likely an important force in other vertically disintegrated industries, and managerial incentives may matter for information gathering even in integrated industries. In the hotel industry, at least, we should be wary of paradigm shifts that place the informational advantage in the hands of upstream parties. However, until chains' demand forecasting becomes sophisticated enough to gather such soft information, this is not an industry poised to experience such structural changes.

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A Identification Details

I here show that the system of equations 7 is invertible. Recall that this system reflects the condition that, for a given guess of noise parameters $\hat{\sigma} \equiv (\hat{\sigma}_1, \hat{\sigma}_2, \ldots, \hat{\sigma}_J)$, and given knowledge of $(z_{p1}, z_{p2}, \ldots, z_{pJ})$, the model-generated variance in prices must equal the data-implied variance in prices:

$$\text{var}_{\hat{\sigma}}(\hat{p}_j|x,\delta) = \widehat{\text{var}}_{\hat{\sigma}}(\hat{p}_j|x,\delta), \quad \forall j.$$

Defining $v_j \equiv \widehat{\text{var}}(p_j|x,\delta)$, and suppressing x and δ as arguemnts, these conditions can also be expressed as

$$\begin{aligned} \text{var}_{\hat{\sigma}}(\hat{p}_j|x,\delta) + \hat{\sigma}_j^2 - v_j = & \quad 0, \forall j \\ \equiv M_j(\hat{\sigma}, v_1) = & \quad 0, \forall j. \end{aligned}$$

Note that v_j can be computed directly from the data. This is a system of nonlinear equations $M(\sigma, v) : \mathbb{R}^{2j} \to \mathbb{R}^j$ that can be written as

$$M(\hat{\sigma}, v) \equiv \begin{bmatrix} M_1(\hat{\sigma}, v_1) \\ M_2(\hat{\sigma}, v_2) \\ \vdots \\ M_J(\hat{\sigma}, v_J) \end{bmatrix} = \mathbf{0}.$$

In the main body of the paper, I showed that the first term of M_j, $\text{var}_{\hat{\sigma}}(\hat{p}_j|x,\delta)$, is increasing in j's own σ. As a result, M_j is increasing in $\hat{\sigma}_j$.

M_j is also increasing in rivals' σ by the following reasoning. The monotonicity assumptions of the model imply that prices are positively correlated across firms; if rival k's σ_k increases, its prices will vary more, and because prices are positively correlated, the variance of the sum of j's rivals' prices (and also their average) increases as σ_k increases.

My next claim is that $\frac{\partial M_j(\hat{\sigma})}{\partial \sigma_j} > \sum_{k \neq j} \frac{\partial M_k(\hat{\sigma})}{\partial \sigma_j}$. That is, condition j changes more from its own σ_j than all conditions k do from changes in σ_j. The first-order effects of an increase in σ_j are (1) to increase the variance of $\hat{p}_j$ by making the implied signal stronger and (2) mechanically through σ_j^2 entering directly into the second term of M_j. The second-order effects are on rivals' conditions: if $\hat{p}_j$ becomes more variable, rival k's expectations over $\hat{p}_{-k}$ become more variable, so rival k's prices become more variable. However, second-order effects must be smaller than first-order effects; otherwise, a small increase in j's price variability would trigger a larger increase in rivals' price variability, triggering an even larger increase in j's price variability, and so on. This would indeed be the case if, for instance, z_{pj} were greater than 1 for each j, but scenarios along these lines would violate the existence criteria of the model. This then guarantees that the Jacobian of system M, $\nabla_\sigma M$, is diagonally dominant.

Finally, because the Jacobian is diagonally dominant, it is positive definite. It follows that there is a unique solution, $\sigma^*(\hat{v})$, to the system $M(\sigma, \hat{v}) = \mathbf{0}$ for any $\hat{v}$.

B Supply Estimation Details

I outline the details of the supply estimation in this appendix. I do this for the more general case, in which within-parent company correlation λ is also estimated. Condition on a market The key variables are common knowledge market demand shifters x_t, non-common knowledge market demand shifters λ_t, and private demand realizations δ_{jt}. The underlying supply model is

$$\begin{aligned} p_{jt} = &\quad z_{0j} + z_{pj}\mathbb{E}[p_{-jt}|x_t, \delta_{jt}, s_{jt}] + z_{\delta j}\delta_{jt} + \nu_{jt} \\ s_{jt} = &\quad \lambda_{jt} + \rho_j \sigma_\lambda(\theta\zeta_{h(j),t} + (1-\theta)\zeta_{jt}) \\ \nu_{jt} \sim &\quad \mathcal{N}(0, \sigma_j^2) \\ \zeta_{h(j),t} \sim &\quad \mathcal{N}(0, 1) \\ \zeta_{jt} \sim &\quad \mathcal{N}(0, 1). \end{aligned} \tag{A.1}$$

and σ_λ is the standard deviation of λ_t, and x_t, λ_t, and δ_{jt} are jointly normal. I make the normalization that λ_t, x_t and $\{\delta_{jt}\}_{j\in\mathcal{J}}$ have mean zero. I first construct the joint distribution of demand shifters and signals. Suppose, for instance, there were three firms, with firms 1 and 2 belonging to the same parent company and firm 3 independent. Write $\tilde{\delta}_{jt} \equiv \delta_{jt} - x_t = \xi_{jt} + \lambda_t$, which is as good as observed by the firms because x_t is common knowledge.

$$
\begin{bmatrix} \xi \\ s_1 \\ s_2 \\ s_3 \\ \tilde{\delta}_1 \\ \tilde{\delta}_2 \\ \tilde{\delta}_3 \\ x \end{bmatrix}
\sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix}
\hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & 0 \\
\hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2(1+\rho_1^2) & \hat{\sigma}_\lambda^2(1+\theta\rho_1\rho_2) & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & 0 \\
\hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2(1+\theta\rho_1\rho_2) & \hat{\sigma}_\lambda^2(1+\rho_2^2) & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & 0 \\
\hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2(1+\rho_3^2) & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & 0 \\
\hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2+\hat{\sigma}_{\xi 1}^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & 0 \\
\hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2+\hat{\sigma}_{\xi 2}^2 & \hat{\sigma}_\lambda^2 & 0 \\
\hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2 & \hat{\sigma}_\lambda^2+\hat{\sigma}_{\xi 3}^2 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & \hat{\sigma}_x^2
\end{bmatrix} \right)
$$

where all of the objects with hats are easily calculated from the data, and all of the objects without hats are parameters to be estimated. Upon observing s_{jt}, x_t, and $\tilde{\delta}_{jt}$, firms form posteriors over s_{-jt}, δ_{-jt} and λ_t. Because all of these variables are jointly normal, the posterior can be computed and is also jointly normal. Furthermore, the expectation of rivals' signals and δ are both linear in $(s_{jt}, x_t, \delta_{jt})$. This means we can write, now for an arbitrary number of firms:

$$\mathbb{E}_1\left[\begin{bmatrix}1\\ s_{1t}\\ \tilde{\delta}_{1t}\\ x_t\\ 1\\ s_{2t}\\ \tilde{\delta}_{2t}\\ x_t\\ \vdots\\ 1\\ s_{jt}\\ \tilde{\delta}_{Jt}\\ x_t\end{bmatrix}|s_{jt},\tilde{\delta}_{jt},x_t\right]=\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&0&1&0\\0&0&0&1\\1&0&0&0\\0&M_{1,2}^{s,s}&M_{1,2}^{\delta,s}&M_{1,2}^{x,s}\\0&M_{1,2}^{s,\delta}&M_{1,2}^{\delta,\delta}&M_{1,2}^{x,\delta}\\0&0&0&1\\ \vdots&\vdots&\vdots&\vdots\\1&0&0&0\\0&M_{1,j}^{s,s}&M_{1,j}^{\delta,s}&M_{1,j}^{x,s}\\0&M_{1,J}^{s,\delta}&M_{1,J}^{\delta,\delta}&M_{1,J}^{x,\delta}\\0&0&0&1\end{bmatrix}\begin{bmatrix}1\\ s_{jt}\\ \tilde{\delta}_{jt}\\ x_t\end{bmatrix}\equiv M_1\begin{bmatrix}1\\ s_{jt}\\ \tilde{\delta}_{jt}\\ x_t\end{bmatrix}. \tag{A.2}$$

where M_1 is derived using the variance-covariance matrix of shifters and signals.[26] It is also useful to define

$$\tilde{M}_1\equiv M_1\odot\begin{bmatrix}0&0&0&0\\0&0&0&0\\0&0&0&0\\0&0&0&0\\1&1&1&1\\1&1&1&1\\ \vdots&\vdots&\vdots&\vdots\end{bmatrix} \tag{A.3}$$

and

[26]Let $\mathbf{x}=\begin{bmatrix}\mathbf{x}_1 & \mathbf{x}_2\end{bmatrix}$ be a random vector with subvectors $\mathbf{x}_1$ and $\mathbf{x}_2$. $\mathbf{x}$ is distributed $\mathcal{N}(\mathbf{0},\begin{bmatrix}\Sigma_1 & \Sigma_{12}\\ \Sigma_{12}' & \Sigma_2\end{bmatrix}$. If we observe $\mathbf{x}_2=x_2$ our posterior expectation over $\mathbf{x}_1$ is $\mathbb{E}(\mathbf{x}_1|\mathbf{x}_2=x_2)=\Sigma_{12}\Sigma_{22}^{-1}x_2$. Because we know the variance-covariance matrix in signals and variables for a given guess of the parameters, we can calculate M accordingly. In this simple example, $M=\Sigma_{12}\Sigma_{22}^{-1}$

$$\tilde{M}_2 \equiv M_2 \odot \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}. \tag{A.4}$$

and so on, where $\odot$ is the element-wise product of matrices. $\tilde{M}_1$ replaces firm 1's beliefs over its own shifters with zeros. Define M_j and $\tilde{M}_j$ analogously. Because prices are linear in the expectations written in A.2, and expectations are linear in signals and variables, the entire system of firms' pricing equations (net of errors) can be written as a system of linear equations:

$$\begin{aligned} p_{1t} = &\quad \hat{z}_{01} + \hat{z}_{s1} s_{1t} + \hat{z}_{\delta 1} \tilde{\delta}_{1t} + \hat{z}_{x1} x_t \\ p_{2t} = &\quad \hat{z}_{02} + \hat{z}_{s2} s_{2t} + \hat{z}_{\delta 2} \tilde{\delta}_{2t} + \hat{z}_{x2} x_t \\ \vdots & \\ p_{Jt} = &\quad \hat{z}_{0J} + \hat{z}_{Js} s_{Jt} + \hat{z}_{\delta J} \tilde{\delta}_{Jt} + \hat{z}_{xJ} x_t \end{aligned} \tag{A.5}$$

where $\hat{z}_{jy}$ is the reduced form coefficient for firm j's prices on variable y. Write $\hat{\mathbf{z}}_\mathbf{j} = \begin{bmatrix} \hat{z}_{0j} & \hat{z}_{s1} & \hat{z}_{\delta 1} & \hat{z}_{x1} \end{bmatrix}$. Then we can rewrite equation A.5 as

$$p_{jt} = \hat{\mathbf{z}}_\mathbf{j} \begin{bmatrix} 1 \\ s_{jt} \\ \tilde{\delta}_{jt} \\ x_t \end{bmatrix}. \tag{A.6}$$

Plugging rivals' reduced-form strategies into the the pricing equation (without errors ν_{jt}), we have

$$
\begin{aligned}
p_{jt} &= z_{pj}\mathbb{E}_j\left[\bar{p}_{-j}|s_{jt}, x_t, \tilde{\delta}_{jt}\right] + z_{\delta j}(\tilde{\delta}_{jt} + x_t) + z_{0j} \\
&= \frac{z_{pj}}{J-1}\sum_{j' \neq j}\mathbb{E}_j\left[p_{j'}|s_{jt}, x_t, \tilde{\delta}_{jt}\right] + z_{\delta j}(\tilde{\delta}_{jt} + x_t) + z_{0j} \\
&= \frac{z_{pj}}{J-1}\sum_{j' \neq j}\mathbb{E}_j\left[\hat{\mathbf{z}}_{j'}\begin{bmatrix}1\\ s_{j't}\\ \tilde{\delta}_{j't}\\ x_t\end{bmatrix}|s_{jt}, x_t, \tilde{\delta}_{jt}\right] + \begin{bmatrix}z_{0j}\\ 0\\ z_{\delta j}\\ z_{\delta j}\end{bmatrix}^T\begin{bmatrix}1\\ s_{jt}\\ \tilde{\delta}_{jt}\\ x_t\end{bmatrix}
\end{aligned}
\tag{A.7}
$$

where the second line is obtained by plugging in the definition of $\bar{p}_{-j}$ and the third line plugs equation A.6 in for each p_{-j} and rewrites the rest of the equation in matrix notation. We can then use equation A.2 and the definition in equation A.3 to rewrite the sum in equation A.7 in matrix notation:

$$
\begin{aligned}
p_{jt} &= \frac{z_{pj}}{J-1}\begin{bmatrix}\hat{\mathbf{z}}_{\mathbf{1}} & \dots & \hat{\mathbf{z}}_{\mathbf{J}}\end{bmatrix}\tilde{M}_j\begin{bmatrix}1\\ s_{jt}\\ \tilde{\delta}_{jt}\\ x_t\end{bmatrix} + \begin{bmatrix}c_j\\ 0\\ z_{\delta j}\\ z_{\delta j}\end{bmatrix}^T\begin{bmatrix}1\\ s_{jt}\\ \tilde{\delta}_{jt}\\ x_t\end{bmatrix} \\
&\equiv \frac{z_{pj}}{J-1}\hat{\mathbf{z}}\tilde{M}_j\begin{bmatrix}1\\ s_{jt}\\ \tilde{\delta}_{jt}\\ x_t\end{bmatrix} + \begin{bmatrix}z_{0j}\\ 0\\ z_{\delta j}\\ z_{\delta j}\end{bmatrix}^T\begin{bmatrix}1\\ s_{jt}\\ \tilde{\delta}_{jt}\\ x_t\end{bmatrix}.
\end{aligned}
$$

where we define $\hat{\mathbf{z}} \equiv \begin{bmatrix}\hat{z}_{01} & \hat{z}_{s1} & \hat{z}_{\delta 1} & \hat{z}_{x1} & \dots & \hat{z}_{xJ}\end{bmatrix}$. Finally, we can use j's own reduced-form pricing equation A.6 to rewrite the above as

$$\hat{\mathbf{z}}_{\mathbf{j}} \begin{bmatrix} 1 \\ s_{jt} \\ \tilde{\delta}_{jt} \\ x_t. \end{bmatrix} = \frac{z_p}{J-1} \hat{\mathbf{z}} \tilde{M}_j \begin{bmatrix} 1 \\ s_{jt} \\ \tilde{\delta}_{jt} \\ x_t \end{bmatrix} + \begin{bmatrix} z_{0j} \\ 0 \\ z_\delta \\ z_\delta \end{bmatrix}^T \begin{bmatrix} 1 \\ s_{jt} \\ \tilde{\delta}_{jt} \\ x_t \end{bmatrix} \tag{A.8}$$

$$\hat{\mathbf{z}}_{\mathbf{j}} = \frac{z_p}{J-1} \hat{\mathbf{z}} \tilde{M}_j + \begin{bmatrix} z_{0j} \\ 0 \\ z_\delta \\ z_\delta \end{bmatrix}^T .$$

Equation A.8 says that the reduced-form supply coefficients for firm j can be expressed as a weighted sum of rivals' reduced-form supply coefficients, plus a constant, where this weighting depends on j's policy parameters $\{z_{pj'}, z_{\delta j'}, z_{0j'}\}$ and the information parameters $\{\{\rho_{j'}\}_{j' \in \mathcal{J}}, \lambda\}$. Stacking these equations of each firm yields a system of $4 * J$ linear equations in $4 * J$ unknowns:

$$\hat{\mathbf{z}} = \frac{1}{J-1} \hat{\mathbf{z}} (\mathbf{z}_p \odot \tilde{M}) + \begin{bmatrix} z_{01} \\ 0 \\ z_{\delta 1} \\ z_{\delta 1} \\ \vdots \\ z_{0J} \\ 0 \\ z_{\delta J} \\ z_{\delta J} \end{bmatrix}^T$$

where $\tilde{M} \equiv \begin{bmatrix} \tilde{M}_1 & \dots & \tilde{M}_J \end{bmatrix}$ and $\mathbf{z}_p = \begin{bmatrix} z_{p1} & \dots & z_{pJ} \\ z_{p1} & \dots & z_{pJ} \\ \vdots & \vdots & \vdots \end{bmatrix}$. This is solved by

$$\hat{\mathbf{z}} = \left(I_{4J} - \frac{1}{J-1} (\mathbf{z}_p \odot \tilde{M}) \right)^{-1} \begin{bmatrix} z_{01} & 0 & z_\delta & z_{\delta 1} & \dots & z_{0J} & 0 & z_{\delta J} & z_{\delta J} \end{bmatrix} \tag{A.9}$$

where I_{4J} is the $4J \times 4J$ identity matrix. The right hand side of equation A.9 is a function of the supply-side parameters and easily-calculated variances of the demand shifters. For a given guess of supply-side parameters Γ, call the implied right-hand side of this equation $\hat{\mathbf{z}}(\Gamma)$. Now, I show how to estimate the reduced-form coefficients. First, we add the pricing errors ν_{jt} back into the reduced-form pricing equation, and then substitute the formula for the signal from A.1:

$$\begin{aligned} p_{jt} = & \quad \hat{z}_{0j} + \hat{z}_{sj} s_{jt} + \hat{z}_{\delta j} \tilde{\tilde{\delta}}_{jt} + \hat{z}_{xj} x_{jt} + \nu_{jt} \\ = & \quad \hat{z}_{0j} + \hat{z}_{sj}(\lambda_t + \sigma_\lambda \rho_j \theta \zeta_{h(j),t} + (1-\theta)\zeta_{jt}) + \hat{z}_{\delta j} \tilde{\tilde{\delta}}_{jt} + \hat{z}_{xj} x_{jt} + \nu_{jt}. \end{aligned}$$

Rearrange to obtain

$$p_{jt} = \hat{z}_{0j} + \hat{z}_{sj} \lambda_t + \hat{z}_{\delta j} \tilde{\tilde{\delta}}_{jt} + \hat{z}_{xj} x_{jt} + \hat{\nu}_{jt} \tag{A.10}$$

where $\hat{\nu}_{jt}$ contains random variation from both, ν_{jt} and the signal, but all of these errors are independent of the demand shifters. As a result, I can estimate $\hat{\mathbf{z}}$ by least-squares regressions of the form

$$p_{jt} = \hat{\mathbf{z}}_{\mathbf{j}} \begin{bmatrix} 1 \\ \lambda_t \\ x_t \\ \tilde{\delta}_{jt} \end{bmatrix} + \hat{\nu}_{jt}. \tag{A.11}$$

For any guess of supply parameters Γ, I can use A.9 to generate the implied reduced-form coefficients $\hat{\mathbf{z}}(\Gamma)$. If I assume $\theta = 0$ (or some other number between 0 and 1), then this enough to identify the model. That is, I can minimize the following objective function

$$\min_{\Gamma} (\hat{\mathbf{z}}(\Gamma) - \hat{\mathbf{z}}) W (\hat{\mathbf{z}}(\Gamma) - \hat{\mathbf{z}})' \tag{A.12}$$

where $\hat{\mathbf{z}}$ are the estimates from regression A.11, and this would be enough to pin down the remaining parameters of the model, up to $\hat{\sigma}_j$, which can be backed out from the variance in prices after estimating the remaining parameters. In my specification, where I assume $\theta = 0$, this is what I do. θ could also be estimated by matching additional "moments." In particular, the covariance matrix of $\hat{\nu}_{jt}$ can identify this more general model. It can be shown that the covariance between $\hat{\nu}_{jt}$ and $\hat{\nu}_{j't}$ is equal to $\hat{z}_{sj}\hat{z}_{sj'}\sigma_\lambda^2$ if j and j' do not belong to the same parent company and equal to $\hat{z}_{sj}\hat{z}_{sj'}\sigma_\lambda^2(1 + \rho_j \rho_{j'} \theta)$ if they do belong to the same parent company. In estimating the more general model, I can stack the conditions in equation A.12 with the condition that model-implied pricing error covariance matrix $\hat{\Omega}(\Gamma)$ equals reduced form error covariance matrix $\hat{\Omega}$, where $\hat{\Omega}$ is the covariance matrix of $\{\hat{\nu}_{jt}\}_{j \in J}$.

As a final note, I choose weighting matrix W in equation A.12 as the inverse of the covariance matrix of $\hat{z}$ from the reduced-form regression A.11.

C Simulation Details

Simulation of counterfactual prices, quantities, and revenues involves the following steps. Let τ index simulation draws.

1. Set counterfactual parameters (e.g., choose ρ_j for each hotel j).
2. Solve for reduced-form coefficients $\hat{z}$ and price error covariance matrix $\hat{\Omega}$ according to the procedures in Appendix B.
3. Draw τ pricing shocks $\hat{\nu}_{jt}^{(\tau)} \sim \mathcal{N}(0, \hat{\Omega})$.
4. Simulated prices $\mathbf{p}_{jt}^{(\tau)} = \hat{z}_j \begin{bmatrix} x_t & \lambda_t & \xi_{jt} \end{bmatrix}' + \hat{\nu}_{jt}^{(\tau)}$
5. Simulate quantities $q_t^{(\tau)} \equiv \{q_{jt}^{(\tau)}\}_{j \in \mathcal{J}}$ given prices $\{p_{jt}^{(\tau)}\}_{j \in \mathcal{J}}$. Because hotels have capacity constraints, I ration consumers in the following manner:
   (a) Use nested logit formula 8 and estimated demand parameters to obtain estimated shares $s_t^{(\tau)} = \{s_{jt}^{(\tau)}\}_{j \in \mathcal{J}}$.
   (b) Use definition of market size $\mathcal{M}_t$ to find quantities: $q_{jt}^{(\tau)} = s_{jt}^{(\tau)} \mathcal{M}_t$.
   (c) Record hotels in nest b that are over capacity: $\mathcal{J}_b^{cap} \equiv \{j \in \mathcal{J}_b : Cap_j < q_{jt}^{(\tau)}\}$. Reallocate excess capacity in nest b, $Excess_t^{(\tau)} \equiv \sum_{j \in \mathcal{J}_b^{cap}} \left[q_{jt}^{(\tau)} - Cap_j\right]$ among remaining hotels. In my main specification, I reallocate excess capacity within-nest according to IIA; if hotel j in nest b is below capacity, it receives additional customers $Excess_t^{(\tau)} \left(\frac{s_{jt}^{(\tau)}}{s_{bt}^{(\tau)}}\right)$. That is, j receives additional customers according to its within-nest share.
   (d) Record hotels that are still over capacity (e.g., through reallocation from other above-capacity hotels) and repeat step (c) until convergence; that is, until there are no more hotels above capacity.

(e) If convergence does not occur (i.e., nest share is larger than nest capacity, so all hotels sell out), move excess capacity to outside good.

6. Generate revenues $r_{jt}^{(\tau)} = q_{jt}^{(\tau)} p_{jt}^{(\tau)}$

7. Average over simulation draws τ and sum over days t to obtain expected annual revenues for each hotel j.

The rationing rule in step 5 is very simple and assumes that there is only within-nest rationing. Alternatively, I could assume a consumer who does not get a room at hotel j in nest b disappears and is replaced by another consumer who books hotel j' according to the nested logit formula, applied only to the set of hotels with remaining capacity (and the outside option). This is the opposite extreme, in which there is the maximum amount of across-nest rationing. The most sophisticated rationing rule would use a hierarchical Bayes technique, as in Train (2001). I may use this technique in future iterations of this paper.

D Additional Figures and Tables

Figures

A.1 Descriptive evidence: price response curves, by parent company type

A.2 Simulated revenues vs. info quality

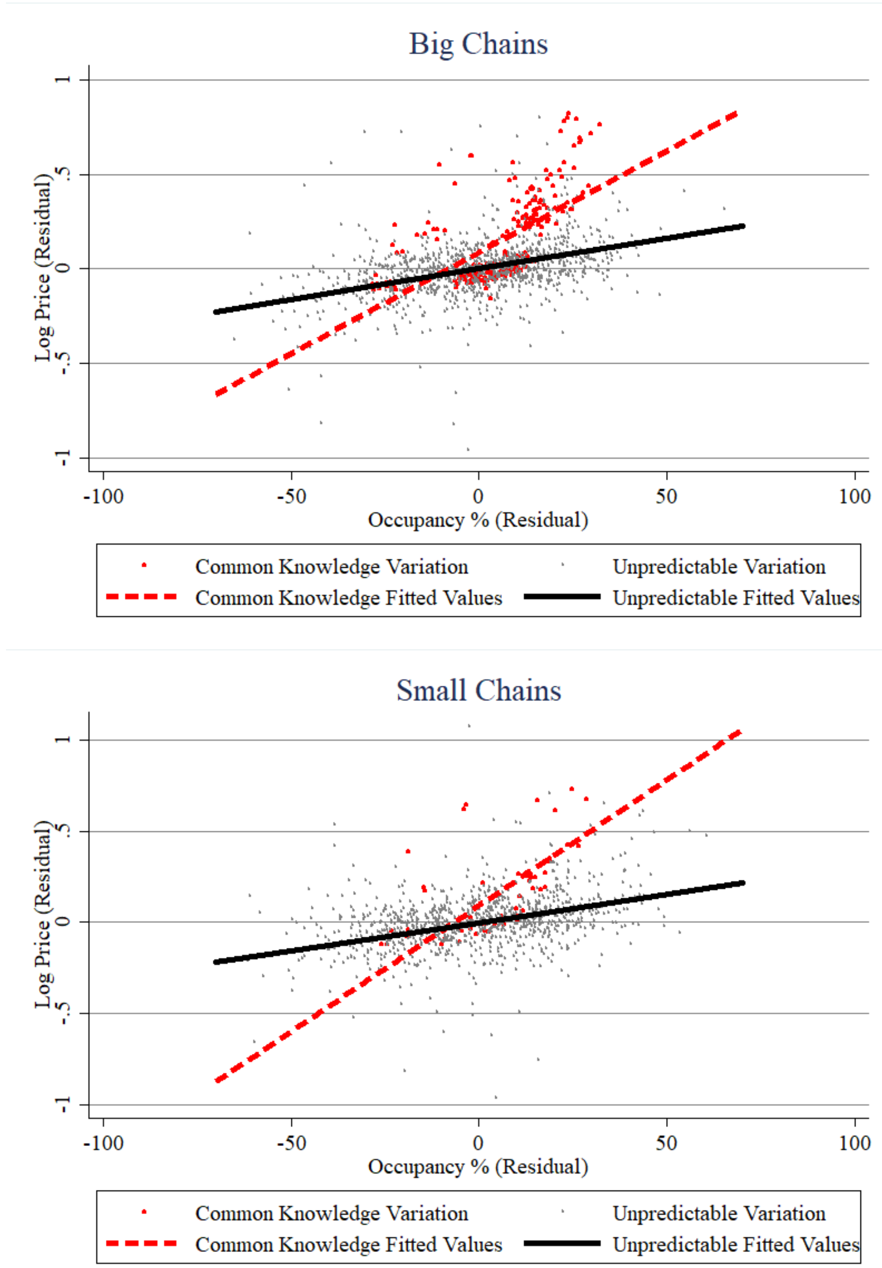
A.3 Gains and losses from switching parent types

Tables

A.1 Demand first stage

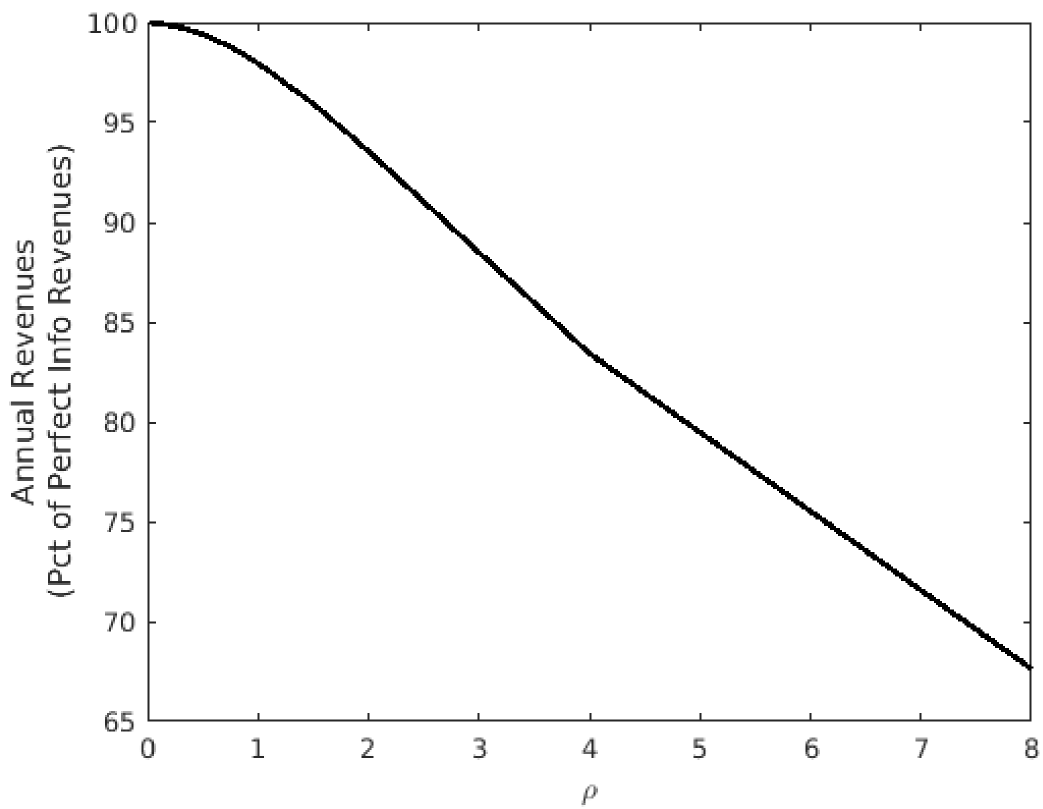
A.2 Cost-of-effort regression

Figure A.1: Descriptive evidence: price response curves, by parent company type



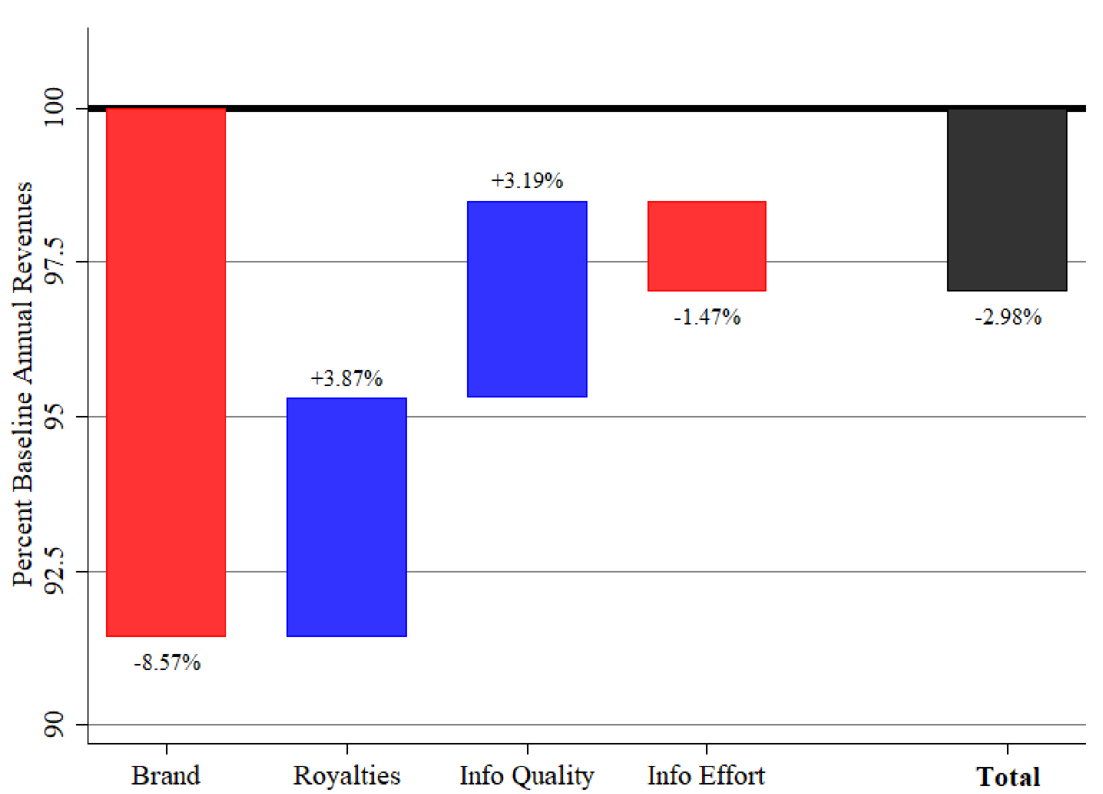
Data source: STR, Inc. The procedure for creating these tables is the same as for Figure 3, except the data are split into "Big Chains" and "Small Chains" according to the classification in 2.

Figure A.2: Simulated revenues vs info quality



Data source: STR, Inc. This figure displays the average annual revenue, across all hotels, for different levels of information quality, holding information quality of all rivals fixed. Annual revenues are simulated for each hotel j at the following values of ρ_j: 0, .25, .5, .75, 1, 1.5, 2, 4, 8, with information equal to estimates for all other hotels in j's market. Simulated revenues were then normalized as fraction of revenues when $\rho_j = 0$.

Figure A.3: Revenue gains and losses, switching from large chain to small



Data sources: STR, Inc and HVS. This figure displays a decomposition of the average change in annual revenues from switching from an upscale large chain to an upscale small chain. “Brand” refers to loss in demand from switching to a lower-quality brand in same quality segment. “Royalties” refers to reduction in royalty payments to parent company as percentage of revenue. “Info quality” refers to expected annual gains from having higher-quality information. “Info effort” refers to increased costs of collecting information, i.e., providing more effort.

Table A.1: Demand Estimates: First Stage

	Estimate (Std. Err.)		
Dependent Variable	ADR	ADR* 1[Weekday]	log Within-Nest Share
Num in Class/100	−0.633***	−0.011	−0.013***
	(0.016)	(0.011)	(0.000)
Num in Class*1[High Demand]/100	0.059***	0.001	−0.005***
	(0.020)	(0.014)	(0.000)
Num in Class*1[Weekday]/100	0.439***	−0.184***	−0.017***
	(0.018)	(0.012)	(0.000)
Owner Size	0.116***	0.462***	−0.007***
	(0.038)	(0.026)	(0.000)
Owner Markets	−0.934***	−1.194***	0.160***
	(0.059)	(0.041)	(0.001)
Parent Share	−4.746**	0.003	0.364***
	(1.834)	1.261	(0.045)
Parent Share*1[High Demand]	62.900***	4.655**	0.327***
	(2.668)	(1.834)	(0.065)
Parent Share*1[Weekday]	−3.633*	−7.160***	0.426***
	(2.136)	(1.468)	(0.052)
F-statistic	409	245	2114
High Demand-Market FE	Y	Y	Y
Day of Week-Market FE	Y	Y	Y
Brand*1[Weekday] FE	Y	Y	Y
Market-Date FE	Y	Y	Y

Data source: STR, Inc.

Table A.2: Cost-of-effort regresssion estimates

Dependent Variable	Marginal Revenue ($000s/yr)
Information Quality	1.048
	(6.246)
Parent Company FE:	
A	−5.518
	(6.699)
B	−10.377
	(6.375)
C	−11.462*
	(6.367)
D	0.613
	(5.673)
E	−6.314
	(5.355)
Omitted Parent Type	Small
Market-Class-1[Weekday] FE	Y

Data source: STR, Inc and HVS. Information quality measured as $\frac{1}{1+\rho}$. Annual marginal revenue calculated from simulations as described in Section 5 and Appendix C. OLS standard errors reported do not account for standard errors from previous steps and simulation error.