

# Markups and Costs under Capacity Constraints: the Welfare Effects of Hotel Mergers

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## Abstract

Hotel chain mergers increase markups through market concentration, but also stand to decrease average costs through added efficiencies. The pass-through of these cost reductions to consumers—versus rising markups—leads to ambiguous welfare effects. This paper constructs an equilibrium model of the U.S. hospitality sector, incorporating a flexible model of costs which captures firm capacity constraints. I show that firms with larger hotel portfolios face lower average costs and softer capacity constraints when approaching full occupancy. In hypothetical merger scenarios, I provide evidence for when efficiencies result in pro-competitive effects. A merger of large chains decreases average costs for merging firms ( $-12.7\%$ ) but harms consumer surplus ( $-2.0\%$ ), while the acquisition of an independent hotel modestly decreases average costs ( $-2.8\%$ ) while raising consumer surplus ( $0.1\%$ ) as efficiencies are passed through.

**Keywords:** Lodging Industry, Mergers, Economies of scale, Antitrust

**JEL Codes:** L11; L13; L22; Z31

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# 1 Introduction

A fundamental problem facing regulatory authorities is how to evaluate proposed mergers, which is more complicated in environments where there are potential cost efficiencies. The hotel sector is one such example: a trend of consolidation has led to large, global chains, which raises concerns about market power,<sup>1</sup> but there is also potential for cost-side efficiencies, as firms with multiple locations in a market may be able to more efficiently manage their hotels’ capacities (“Revenue Management”).<sup>2</sup> This paper aims to provide evidence on the quantitative importance of scale economies in the US hotel industry, and specifically whether they are large enough to offset the consumer welfare losses resulting from merged firms’ increased market power. Examining these merger effects can better inform regulators’ presumptive merger screens and consumer protection in this sector.<sup>3</sup>

I estimate a rich model of competition with capacity constraints—in which joint ownership creates efficiencies—in order to study mergers and other changes in the sizes (i.e. the number and capacity of owned hotels) of firms in the US hotel sector, and address two questions. First, I measure the efficiencies achieved by increasing the number of rooms and properties held by a given hotel firm, and compare them to the magnitudes of the estimated markups for different firm sizes. Second, I quantify the net welfare effects—on consumers and on the full market—of mergers between firms in order to provide guidance for antitrust policy. Specifically, I model two classes of merger with policy relevance: large chain-to-chain consolidations, which commonly face regulatory attention; and smaller acquisitions by large firms, which may be overlooked by competition authorities.<sup>4</sup>

Costs and consumer welfare are not directly observable in the available data. To identify these values, I construct an equilibrium model of nightly supply and demand in the hotel sector.<sup>5</sup> The model allows me to estimate the magnitudes of the offsetting markup and cost effects, and calculate changes in consumer welfare. Hotel firms, which I define as the parent

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<sup>1</sup>Roper (2018) presents a summary of these developments in the hotel industry.

<sup>2</sup>In Section 2.2, I describe these systems in more detail.

<sup>3</sup>Efficiencies—particularly merger-specific efficiencies—are listed in in Section 10 of the [U.S. Department of Justice and Federal Trade Commission \(2010\)](#) (henceforth Merger Guidelines). In cases with capacity constraints, mergers among hospitals have made reference to both administrative efficiencies and fuller utilization of available beds (e.g. U.S. v. Carillon Health System, summarized by [Kwoka and White \(1999\)](#)).

<sup>4</sup>The under-enforcement of smaller mergers that drive consolidation has been discussed in work such as [Wollman \(2021\)](#) in the healthcare sector.

<sup>5</sup>See [Gandhi and Nevo \(2021\)](#) for an overview of estimating a demand model to recover marginal costs and markups.

company (e.g. Marriott International, Hilton Hotels & Resorts, etc.), own and operate hotels across metropolitan statistical areas (MSAs) and market segments; this paper examines mergers within the same market.<sup>6</sup> These market segments are categories comprised of the chain scale of hotels (an industry measure of quality, such as Upscale or Luxury) and their location (e.g. whether the segment is downtown, or near an airport). A merger of hotel firms hence affects the share of properties and rooms the combined firm operates, both within and across segments in an MSA.

I estimate the model with data from STR LLC, who provide nightly hotel-level prices—average daily rate (ADR)—and the quantities of rooms sold and available for 1,561 hotels in 15 MSAs from 5 different states, from 2014 to 2018. Individual hotels are identified but are anonymous. Observed prices are the average rate paid by all guests staying on a given night. STR also provides pseudonymous firm-ownership data at the monthly level, allowing for changes in parent company ownership to be tracked without identifying the individual hotels. Daily-level observations provide extensive variation in observed demand: occupancy varies between 0.18% and 100%, with a mean of 64%, and 5.4% of hotel-nights are above 99% occupancy (3.6% at 100% occupancy).

Using these data, I estimate a nested logit model of consumer demand, where consumers choose among the set of market segments nested by location category. On the supply side I employ a model of Cournot competition among hotel firms, where firms choose nightly segment-level quantities in each segment where they operate hotels. The key feature is that the firm faces a within-segment soft capacity constraint: the marginal cost curve is constant up to an occupancy rate threshold, above which it is convex and increasing. I model the firm’s occupancy rate threshold as a function of firm size (the number and capacity of owned hotels in the segment), flexibly allowing size variation to drive variation in the nonlinear marginal cost at high occupancy. This approach has two advantages. The first is that—unlike a more literal vertical hard constraint—the cost curve is continuous and differentiable at all points, which provides tractability in solving for counterfactual equilibria. Second, the literature on hotel pricing has already noted that the hotel’s response to capacity does not begin at the hard constraint, but rather increases as it approaches it (Cho, Lee, Rust, and Yu (2018)). The soft constraint approach has been applied in several other settings: Ryan (2012) and Fowlie, Reguant, and Ryan (2016) estimate this constraint in the cement sector, and Farronato and Fradkin (2022) calibrates a similar model for hotels.<sup>7</sup>

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<sup>6</sup>At this time I abstract from questions related to franchising or third-party management firms.

<sup>7</sup>In Section 2.2, I discuss this modeling approach in the context of hotel revenue management, and the

In my results, I find that marginal costs are \$52 higher at 99% occupancy than at 60% occupancy for an independent hotel. I show that firms operating more properties in the same segment face lower marginal costs at high occupancy rates, in line with prior literature that mergers can slacken the impact of a capacity constraint.<sup>8</sup> A firm of 3 hotels cuts their marginal costs by \$9.20 at low occupancy relative to an individual hotel, and this gap widens to a reduction of \$19.67 at full occupancy. These results vary by market segment: airport hotels face the least-tight constraints, while downtown hotels respond earliest to capacity constraints. Last, I explore the unilateral upward pricing pressure from a range of merger sizes: these effects are a useful predictor of the price effects from a merger (Miller, Remer, Ryan, and Sheu (2017)). In mergers of 2 or 3 independent hotels, cost reductions outweigh changes in markups. In all other cases, prices face upward pressure.

Finally, I assess the outcomes of counterfactual hypothetical mergers through a series of merger simulation exercises.<sup>9</sup> I begin by constructing a range of simulated markets in order to test a varied universe of mergers between firms of different sizes and market-segment overlap, under different conditions of demand. I find that while total surplus remains constant or even increases, consumer surplus falls in the size of the merger as measured by the change in the Herfindahl-Hirschman Index (HHI). Only the smallest mergers—those between independent hotels with *de minimis* effects on market concentration—result in consumer gains. This result persists in markets which are at higher or lower market concentration, including those levels which would prompt regulatory scrutiny under the Merger Guidelines. The negative impacts on consumers are amplified when firms overlap across multiple market segments: economies of scale are only earned locally, while market power effects impact all other segments.

To demonstrate these results in real-world data, I simulate the outcomes of two mergers in Madison, WI: one between large chains, and one of a chain acquiring an independent hotel. Taking pre-merger quantities, the former merger raises HHI by nearly 400, resulting in a moderately concentrated market with HHI in excess of 1,500.<sup>10</sup> I find that the mergers would have the effects predicted by the previous exercise: they raise total surplus by

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intuition behind this channel of efficiency.

<sup>8</sup>Kalnins, Froeb, and Tschantz (2017) discuss the potential positive quantity effects of mergers in the context of capacity constraints.

<sup>9</sup>Farrell and Shapiro (2018) provide an overview of the 2010 Horizontal Merger Guidelines and the use of merger simulation in retrospect.

<sup>10</sup>This merger would be a candidate for investigation under the Merger Guidelines but is not large enough to guarantee enforcement.

7.7% and 5.2%, and while the large chain merger decreases consumer surplus by 2.0%, the small acquisition increases consumer surplus by 0.1% (a de minimis amount that nevertheless reinforces that efficiencies can be pro-competitive in the horizontal merger setting). I estimate a fall in average costs within the merged firm. In the former case, this effect is outweighed by increases in markups such that capacity utilization falls, while the opposite holds in the latter case where utilization rises, suggesting that the efficiencies outweigh changes in markups. These outcomes reinforce the importance of regulatory scrutiny of the hotel sector, which continues to undergo aggregation, and cast doubt on the importance of efficiency-based arguments as a defense for larger chain mergers.

This paper contributes to the literature in three main areas. First, this paper adds to studies of oligopolistic competition under capacity constraints, and how these constraints can be modeled and estimated. As previously mentioned, the use of convex marginal cost curves to reflect capacity-constrained behavior has been shown in [Besanko and Doraszelski \(2004\)](#), [Ryan \(2012\)](#), [Fowlie et al. \(2016\)](#), and [Farronato and Fradkin \(2022\)](#). These approaches provide tractability in approaching counterfactuals where data- and computation-intensive approaches to unobserved choice sets such as [Conlon and Mortimer \(2013\)](#) or [Agarwal and Somaini \(2022\)](#), or explicit dynamic modeling such as [Cho et al. \(2018\)](#), [Gedge, Roberts, and Sweeting \(2020\)](#), or [Williams \(2022\)](#) would be infeasible. This paper exploits the clearly observable capacity constraints present in the hotel industry, and incorporates these constraints—and hence an approximation to the outcomes of the dynamic models—into an equilibrium model that assesses a market-level counterfactual.

While this paper takes a static approach to modeling supply and demand, it is worth noting related dynamic studies that bear similarities. Specific to the hotel sector, [Cho et al. \(2018\)](#) estimate a model of dynamic pricing for individual room-nights, incorporating a consumer arrival process, demand expectations, and available capacity. This approach allows for resolving the inherent endogeneity of prices and quantity, and the challenge of unobserved choice sets as consumers arrive when rooms are unavailable.<sup>11</sup> However, such dynamic models are challenging to estimate and may not be suitable for market-level counterfactuals, focusing instead on recovering the pricing behavior of a single hotel and investigating adjustments to the pricing rules involved. Additionally, estimating such

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<sup>11</sup>This latter problem, addressed explicitly via second-choice data by [Conlon and Mortimer \(2013\)](#) and through the estimation of latent, unobserved choice sets by [Agarwal and Somaini \(2022\)](#), stands to bias recovered substitution patterns if otherwise ignored. On the other hand, [Berry and Jia \(2010\)](#) provide evidence that the bias is small in data where the choice set is aggregated and shares are not overly large.

models requires proprietary data on bookings and cancellations that are not available at the market level.

Second, I add to a growing body of work on the hotel sector relating to its operation and regulation. [Kosová, Lafontaine, and Perrigot \(2013\)](#) and [Hollenbeck \(2017\)](#) discuss the ramifications of hotel organizing via chain and franchise structures. [Mazzeo \(2002\)](#), [Lewis and Zervas \(2019\)](#), and [Armona, Lewis, and Zervas \(2021\)](#) provide examples of measuring supply and demand for hotel rooms. [Farronato and Fradkin \(2022\)](#) takes an aggregated approach to explore the effects of Airbnb, showing that flexible peer supply absorbs demand volatility. [Kalnins et al. \(2017\)](#) have previously shown with reduced-form evidence that mergers can increase occupancy. This paper quantifies the economies of scale and cost efficiencies in order to explore their ramifications in policy experiments.

Finally, there is an extensive body of literature on merger efficiencies and their relation to antitrust enforcement. Numerous researchers ([Whinston \(2007\)](#), [Carlton \(2009\)](#), [Ashenfelter, Hosken, and Weinberg \(2013\)](#)) have noted the need for more data on merger outcomes to guide antitrust decisions and reform: this paper adds evidence in the novel case of mergers of capacity-constrained firms where efficiencies may offset market power increases.<sup>12</sup> [Bhattacharya, Illanes, and Stillerman \(2023\)](#) examine a panel of mergers to assess their effects, noting that in many cases—potentially those engaging in dynamic pricing or with overlapping distribution networks—mergers have price-reducing effects. Furthermore, considering merger-specific efficiencies—and hence the trade-offs inherent in market concentration—relates to the question of whether antitrust enforcement has been overly lax. A body of literature examines agency decisions ([Kwoka \(2014\)](#), [Scott Morton \(2019\)](#), [Shapiro \(2021\)](#), [Nocke and Whinston \(2022\)](#), [Rose and Shapiro \(2022\)](#)). [Wollman \(2021\)](#) considers the case of sequences of small mergers which add up to larger consolidations in the healthcare industry: a similar pattern of small acquisitions is occurring in the hotel industry.

In [Section 2](#), I discuss relevant institutional details of the hotel industry. [Section 3](#) discusses the available data and explores descriptive patterns related to the identification of the model. In [Section 4](#), I outline the design and estimation of the structural model, and present the results in [Section 5](#). [Section 6](#) simulates a hypothetical merger and estimates the quantity and welfare effects using the model parameters. I conclude with a discussion in [section 7](#).

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<sup>12</sup>[Williamson \(1968\)](#) notes the importance of economies of scale in horizontal mergers.

## 2 Industry and Policy Background

In this section, I summarize key features of the industry, and relate them to the topic of mergers and efficiencies.

### 2.1 Industry Background

Hotel firms can be divided into two categories: independent firms which control a single property, and larger chain firms which manage a number of properties, usually under one or more brand lines (e.g. Hilton and Conrad, Hilton Garden Inn, Waldorf Astoria). As of 2023, there are eight major global hotel chains: AccorHotels, Carlson Rezidor, Hyatt, Hilton, Marriott, InterContinental Hotel Group (IHG), Wyndham, and Choice. The focus of this paper is on these (and other) hotel parent companies. Many of these firms rely heavily on franchising or the hiring of management companies for day-to-day operations, but the analysis below abstracts away from these considerations.

Hotel properties (and brands) can be organized into chain scales, a categorical ranking of quality that groups hotel chains by their average daily rates (ADRs). Independent hotels, which do not have a chain scale, can be matched to these tiers by their respective ADR relative to chain-affiliated hotels in their geographic proximity. Figure 1 displays the distribution of rooms across the US by chain scale, leaving independent hotels broken out separately. Hotel chain scale therefore reflects a useful ordinal proxy for quality. Some examples of common chains included in each scale are listed in Table 1.

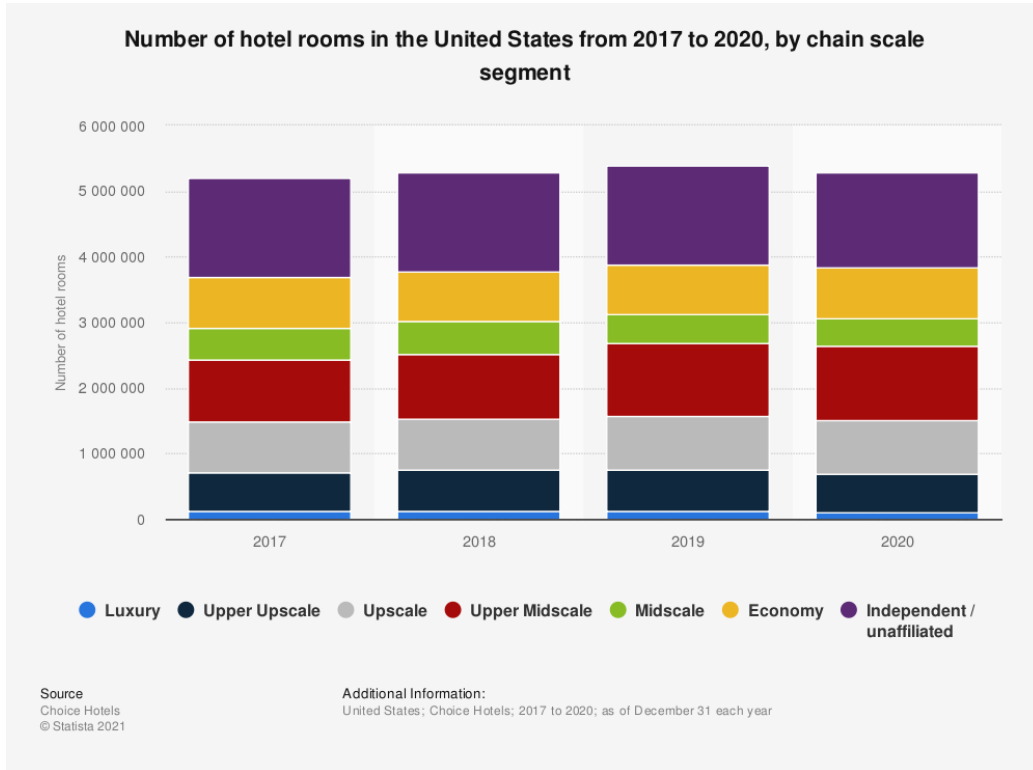
Table 1: Examples of Hotel Chains by Chain Scale

Chain Scale	Examples
Luxury	Four Seasons, Grand Hyatt, Park Hyatt, St. Regis, W Hotels
Upper Upscale	Autograph Collection, Embassy Suites, Hyatt, Marriott, Westin
Upscale	AC Hotels by Marriott, Allegro, Hilton Garden Inn, Wyndham
Upper Midscale	Best Western Plus, Comfort Inn, Hampton, Holiday Inn, Wyndham Garden Hotel
Midcale	Avid, Best Western, Candlewood Suites, Quality Inn, Ramada
Economy	Days Inn by Wyndham, Econo Lodge, Super 8 by Wyndham

This paper will use “Class” to denote chain scale with accordingly ranked independent hotels.

The formation of large hotel parent companies has involved two types of mergers: larger firm-to-firm mergers, and smaller acquisitions of individual properties or brand lines. One example of a large-scale consolidation is the high-profile merger of Marriott International

Figure 1: Hotel Rooms by Chain Scale in the US



and Starwood Hotels & Resorts, which culminated on September 23, 2016, created the largest hotel company in the world with over 5,700 properties and 1.1 million rooms (Dogru, Erdogan, and Kizildag (2018)). This merger faced regulatory scrutiny before being approved without contest in the US. It is far from the only case - Table 2 summarizes a number of other mergers of firms from 2014 to 2018 in the hospitality industry. More recently, in 2022 Choice acquired Radisson, and in 2023 it made a move to acquire Wyndham.<sup>13</sup>

Many other mergers, however, involve one of the global chains (or even a smaller regional chain) acquiring a brand line or set of independent hotels. These consolidations are not commonly subjected to regulatory oversight owing to their comparative small size in regional or national markets. The properties themselves may be brought under new management or, frequently, operated as franchises such that the hotel chain gains a steady flow of franchise fees which are insulated from market volatility. The franchise also gains from this arrangement with the substantial demand boost of brand recognition (Hollenbeck (2017)) and added discoverability of the property.

<sup>13</sup>Choice’s offer of approximately \$9.8 billion for Wyndham on October 17, 2023 was ultimately rejected.



Table 2: Sample Mergers in the US Hospitality Sector

Acquiring Company	Acquired Company	Year	Deal Value
InterContinental Hotels Group	Kimpton Hotels + Restaurants	2014.12	\$430 million
Wyndham Hotel Group	Dolce Hotels & Resorts	2015.02	\$57 million
Red Lion Hotels Corporation	GuestHouse International, Settle Inn & Suites	2015.04	\$8.5 million
Marriott International	Starwood Hotels & Resorts Worldwide	2015.11	\$13.6 billion
Red Lion Hotels Corporation	Vantage Hospitality	2016.09	\$23 million
Hyatt Hotels Corp.	Miraval Group	2017.01	\$215 million
Wyndham Hotel Group	AmericInn	2017.07	\$170 million
Choice Hotels International	WoodSpring Suites	2017.12	\$231 million
Wyndham Worldwide	La Quinta Holdings	2018.01	\$1.95 billion
Red Lion Hotels Corporation	Knights Inn	2018.04	\$27 million

Source: [Law, Lee, Xiao, and Zhang \(2020\)](#)

## 2.2 Revenue Management and Efficiency

The hotel sector, like other industries with constrained and finite supply (airlines, car rentals, etc.) widely utilizes revenue management systems (RMS) to ration capacity.<sup>14</sup> The use of these algorithmic pricing tools results in a data-generating process that is difficult to model. These tools are black boxes, which vary across hotels in objective, implementation, and the data available to target their outcomes. Common assumptions, such as observing an equilibrium in the data, may also be invalid as agents have unknown information, assumptions, and objective functions.<sup>15</sup> The operations literature has delved into theory and applications of revenue management systems ([Kimes \(1989\)](#) and [McGill and Van Ryzin \(1999\)](#) provide discussion from airlines and transportation), while in economics attempts to recover or approximate algorithmic pricing outcomes have been made, using dynamic models ([Cho et al. \(2018\)](#), [Gedge et al. \(2020\)](#), and [Williams \(2022\)](#)) and agent-based approaches (see [Aguirregabiria and Jeon \(2020\)](#) for an example).

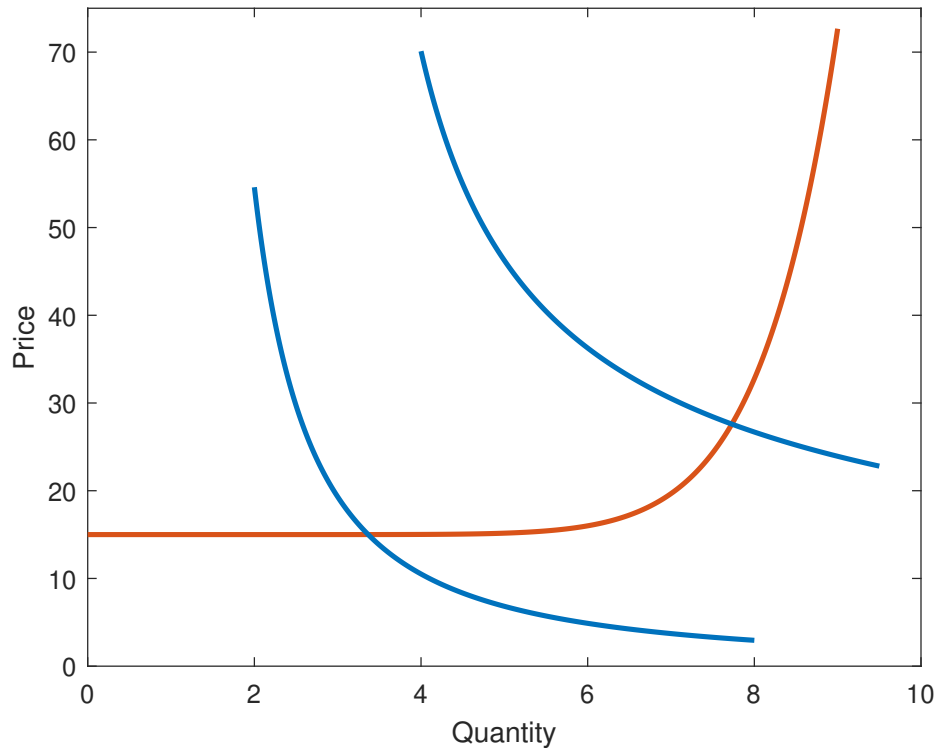
In order to reflect these dynamics while allowing for the computation of counterfactual market equilibria, I take a static approach to modeling capacity constraints via the firm’s cost function. As noted by [Cho et al. \(2018\)](#), an approximation of the dynamic pricing heuristic is for firms to unilaterally deviate from competitive pricing when the risk of stockout reaches some threshold, in order to ration its remaining rooms. This can be interpreted as if the firm continued to price competitively while facing a marginal cost curve which increases

<sup>14</sup>The introduction of [Cho et al. \(2018\)](#) provides a thorough summary of the hotel industry landscape with respect to these tools. [Kimes \(2017\)](#) summarizes the current and projected future use of revenue management in the hotel sector.

<sup>15</sup>[Aguirregabiria and Magesan \(2020\)](#) discusses model-based approaches to non-equilibrium environments.

steeply after this threshold in occupancy. In aggregate, the outcomes of this model approximate the dynamic model, and capture the effect of capacity constraints—through revenue management—on market outcomes. Figure 2 plots such a supply curve, and demonstrates two hypothetical equilibria at different levels of demand. Equilibrium prices rise steeply with quantity when the intercept lies on the convex, increasing segment of the supply curve.

Figure 2: Supply and Demand with Convex Marginal Costs



In this context, marginal cost is in part an abstract value: a combination of the operational costs of selling a room and of rising opportunity costs owing to the option value of rooms when occupancy is higher. As discussed by [Kalnins \(2006\)](#) and [Farronato and Fradkin \(2022\)](#), the firm’s marginal costs in the model should not be taken as the actual expenditures per night for the firm. Firms set prices based on a number of considerations that factor into their perceived costs, such as the amortization of fixed or contracted long-term costs over expected room sales, or expected added revenue and costs through non-room amenities. Additionally, hotels may enforce a minimum price threshold due to reputational concerns which exceeds the marginal cost of selling a room. I treat recovered costs simply as the minimum price threshold under which hotels would be unwilling to sell a room at all. This

also suggests that the estimated markups are not explicit in accounting terms.

Given this, the efficiency channel can be described as follows. When a hotel is near its constraint, the opportunity cost of selling a room is high due to its increased option value, and the firm requires sharply higher prices in order to sell its finite remainder of rooms. The penalty to accepting too-low prices is to reach stockout and forfeit the revenues of excess demand. When the same firm owns some proportion of the alternatives, a portion of that excess demand is recaptured. The firm may, under this circumstance, be more willing to sell its final rooms at lower prices: the impact of the capacity constraint slackens, and the firm can raise quantities at the same prices, *ceteris paribus*.<sup>16</sup> As such, there is a nonlinear cost efficiency where larger firms may raise output and further reduce average costs during high-demand periods where consumers are most exposed to higher prices.

### 2.3 Policy Background

The issue of efficiencies as a relevant defense for a potentially anti-competitive horizontal merger is well known ([Williamson \(1968\)](#)), and regulators face a trade-off in mergers which are able to earn economies of scale yet also raise market power. The 2010 Horizontal Merger Guidelines Section 10 allow for the existence of “merger-specific efficiencies” which are unlikely to be accomplished in the absence of the merger. An argument that this paper does not explore is whether hotels could achieve the same efficiencies through contracting over quantities: it is plausible that coordination in quantities would lead to tacit coordination in prices regardless. This paper thus considers all of the efficiencies estimated to be merger-specific.

Merger efficiencies need to be verifiable to be considered a defense: in markets where efficiencies are less tangible this threshold is harder to reach ([Goettler and Gordon \(2011\)](#) provides one such example of efficiencies in innovation). The Merger Guidelines note “efficiencies resulting from shifting production among facilities formerly owned separately” specifically as a case which is “more likely to be susceptible to verification.” While these efficiencies are known to researchers and regulators, the quantitative evidence for their magnitudes is idiosyncratic to industries and hence more scarce. Additionally, there is a modicum of skepticism on the legal side of antitrust: the 2023 proposed draft merger guidelines strikes a harder tone in Section 3, noting that “Congress and the courts have indicated their pref-

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<sup>16</sup>A Monte Carlo test in [Appendix A](#) demonstrates this theoretical outcome.

erence for internal efficiencies and organic growth” and that merger economies “cannot be used as a defense for illegality.”<sup>17</sup>

Aside from their identification, efficiencies matter because they result in nuanced merger outcomes which may or may not correspond to the Agencies’ presumptive screens. The Merger Guidelines show concern at mergers resulting in “moderately concentrated” markets (HHI of at least 1,500) with a change in HHI of at least 100, and presumes consumer harm for mergers in “highly concentrated” markets (HHI of at least 2,500) with changes in HHI of 100-200. The structural presumption applies ex ante: [Bhattacharya et al. \(2023\)](#) examine a broad set of retail mergers and investigate how the presumptive screen would perform ex post, finding high variation in the actual results of mergers across HHI changes.<sup>18</sup> There is also subtlety in merger strategy: a firm may engage in multiple small mergers ([Wollman \(2021\)](#)) that individually are below the threshold of regulation and where scale effects may be non-monotonic. The Draft Merger Guidelines note that Agencies have begun to take this into account: Section 9 suggests Agencies may examine the series as a whole.

### 3 Data and Descriptive Evidence

In this section, I briefly describe the paper’s data, and discuss key descriptive facts which motivate the design and identification of the structural model.

#### 3.1 Data Source

The primary data source is STR LLC who provide hotel-day level data. This panel includes the nightly average daily rate (ADR) and hotel occupancy rates for 1,561 hotels from 2014-2018. The data cover MSAs in Indiana, Illinois, Missouri, Texas, and Wisconsin. Hotels, chains, and parent companies in the data are identified by unique codes but are anonymous: no names, addresses, or specific identifying information is provided.

As hotels in the data cannot be matched to real-world properties, the characteristics provided for the hotels are limited. I observe the hotel’s chain scale—an industry measurement

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<sup>17</sup>U.S. Department of Justice and Federal Trade Commission (2023), henceforth Draft Merger Guidelines.

<sup>18</sup>[Kwoka \(2016\)](#) notes two types of errors in the presumptive screens: blocking a pro-competitive merger (“Type I”) or failing to block an anti-competitive merger (“Type II”).

for the hotel’s quality tier based on their ADR—indicators for what type of location the hotel is at (airport, resort, urban, interstate, etc) and its categorical number of rooms, and the MSA the hotel is located in. Hotel parent company details are observed at the monthly level, capturing variation (cross-sectionally and over time) in firm size due to mergers and acquisitions.

### 3.2 Descriptive Evidence

The data contain two key sources of variation over time and across markets which are central to the structural model: variation in segment prices and quantities, and variation in firm size. I first describe the variation in prices and occupancy rates in the data. I discuss this at the segment-MSA-night level: in Section 4 I discuss the reasons for this level of aggregation. Table 3 displays the distribution of prices and occupancy rates.

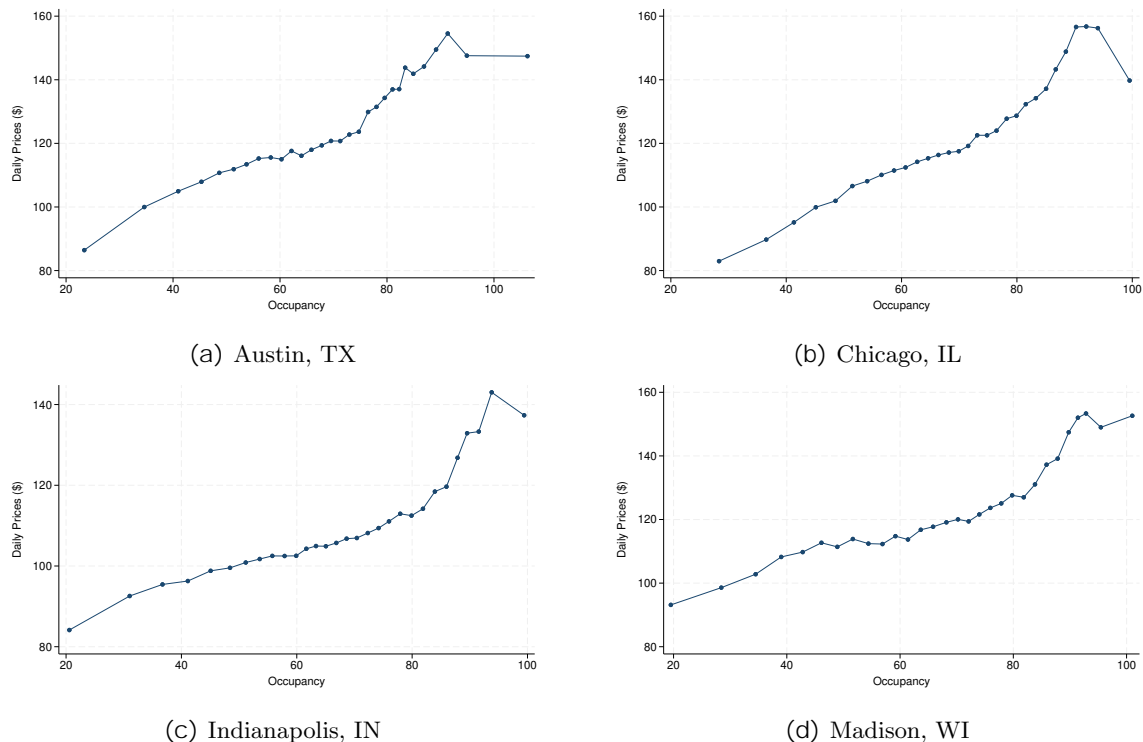
Table 3: Distribution of Prices and Occupancy Rates

Percentile	Prices			Occupancy		
	5th	50th	95th	5th	50th	95th
Luxury	134.15	206.59	305.39	24.40	71.34	98.38
Upper Upscale	96.49	136.08	201.04	31.76	74.56	97.71
Upscale	78.58	110.58	160.39	32.47	72.31	97.41
Upper Midscale	64.24	94.18	144.18	33.97	67.07	96.72
Midscale	51.09	70.19	103.78	23.45	59.04	95.35
Economy	43.94	54.92	93.49	32.27	57.52	88.90
Airport	45.66	85.15	150.46	35.42	69.66	97.71
Urban	50.56	88.34	181.63	27.91	60.72	94.85
Other	54.95	121.36	243.15	29.75	69.41	97.41

Observations include 15 MSAs from 2015-2017 and represent the sample used for model estimation. Observations are at the segment-MSA-night level, summarized by Class and location type.

The assumption that cost curves are increasing and convex cannot be directly observed in the data, as observed equilibrium values are jointly determined by supply and demand. However, as Figure 2 suggests, the pattern of outcomes in the data is still driven by this feature of the market, and hence the presence of these soft capacity constraints is strongly suggested by the observed variation in the data. Figure 3 presents binned scatterplots of prices and occupancy at the daily market-segment level for four major MSAs, controlling for segment-level fixed effects: each plot hence displays the residual prices and quantities, plus the sample means. Prices increase more steeply as market segments approach full occupancy rates. A possible explanation for the flattening of the relationship at full occupancy is that

Figure 3: Relationship Between Prices and Occupancy Rates



these observations may correspond to idiosyncratic events which have atypical pricing.

Table 3 shows the variation in prices and occupancy across market segments. The modeling assumption that segments can be aggregated assumes that hotels and firms display limited variation in prices within segments. The Class-level coefficient of variation by daily MSA-segment is included in Appendix Figure 4. On average, standard deviations within market segments are approximately 0.2 of the mean. Luxury hotels see the widest variation, an intuitive observation as luxury hotels are the most varied and have the widest variance in per room prices at a single property. One interpretation of this statistic is that the aggregated price measures incorporate some degree of measurement error. Future version of this paper will discuss this point further with regards to its implications on the model estimation.

Next, I discuss the variation in firm size in the data, which is necessary for the identification of economies of scale. In Table 4, I report the distribution of the number of properties, number of rooms, and number of market segments operated by each firm compared to the market-level distribution. The median firm is independent, operating only one property. However, there is a wide range of firm sizes even within single segments, as presented in

Figure 4: Distribution of Segment-Level Hotel and Room Counts by Firm

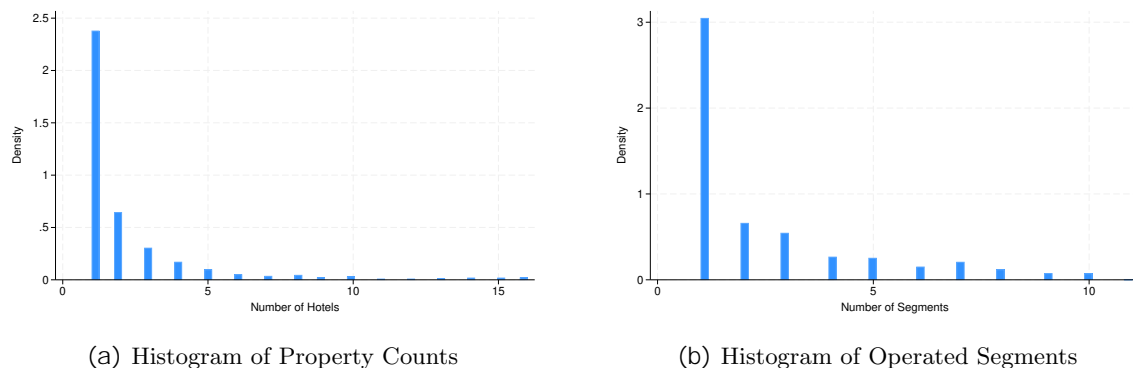


Figure 4. Aside from identifying scale effects, variation in firm size is important as it permits the analysis to credibly test hypothetical mergers that are not “out of sample.” It would be unrealistic if, for example, a simulated merger created a firm of an unprecedented size such that the model might not be invariant to changes of this magnitude. The long right tail of firms’ sizes suggests that a range of merger sizes can be reasonably simulated, focusing on bilateral chain mergers and bilateral or sequential acquisitions of independent firms.

Table 4: Distribution of Number of Properties and Rooms

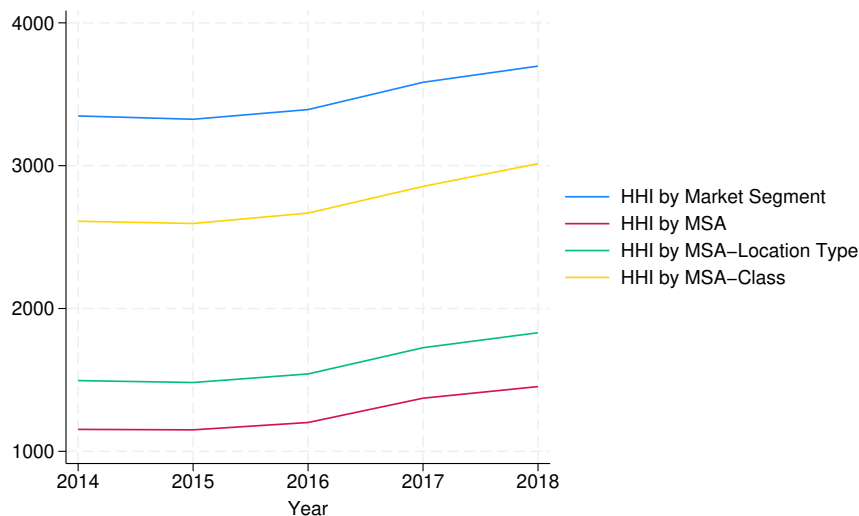
	Parent Companies			Market		
	5th	50th	95th	5th	50th	95th
Hotels per Segment	1	1	8	1	4	37
Rooms per Segment	35	225	1000	100	670	4075
Segments Operated	1	1	7	2	14	17

Observations include 15 MSAs from 2015-2017 and represent the sample used for model estimation.

The hospitality sector has been consolidating over the past several decades (Roper (2018)). This is driven by two factors: the consolidation under large, global hotel chains (see Section 2 for examples in the data sample), and the expansion of franchising as a lower-risk method for large chains to enter new markets. From 2014 to 2018, the firm-segment average number of rooms has risen from 289 to 326, while the firm-segment property count has also risen from 2.48 to 2.86. Figure 5 demonstrates the resulting increases in mean HHI given four market definitions: the MSA, the MSA-Class, MSA-Location, and MSA-Class-Location (segment), where I use firms’ share of capacity as the relevant variable. In 2018, this suggests that the average HHI across days and MSAs is slightly below the Merger Guidelines’ screen for “moderately concentrated”.<sup>19</sup>

<sup>19</sup>The public draft of the agencies’ updated merger guidelines places the threshold for structural pre-

Figure 5: Trends in HHI



A final motivating fact is the presence and effects of existing mergers in the data. Owing to the anonymity of parent companies, I cannot perform a merger retrospective in the paper. However, I draw on the observations of [Armona et al. \(2021\)](#), who perform an event study on the merger of Marriott and Starwood in several US states using an index for the exposure of a given geographical market and class segment to the merger. The authors find that there are substantial price decreases following the completion of the merger in market segments where the merger had high exposure, relative to segments in the same geographical market without exposure. They attribute these effects to cost reductions related to administrative centralization (see [Dogru et al. \(2018\)](#)). I take this as motivating evidence for the presence of cost efficiencies following mergers which may be passed through to consumers.

## 4 Model and Estimation Strategy

In this section, I discuss the model of consumer demand, firm supply, and their identification and estimation. I first discuss the demand model, through which I estimate markups and recover marginal costs from observed prices. Appendix B lists the equations for markups

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sumption at 1,800 or a market share of 30%, given a change in HHI of at least 100. This replaces a moderate concentration threshold at 1,500 and a high concentration threshold at 2,500, with changes in HHI of at least 100.



and demand derivatives from the demand model. Using these recovered costs, I use the supply model to estimate the cost function and the relevant parameters for measuring cost efficiencies.

## 4.1 Demand

Consumers make discrete choices over lodging options  $h$  and an outside option ( $u_0 = 0$ ) each MSA-night  $n$ . The product space of segments  $h$  is defined by categorical quality  $s$  and location  $\ell$ . I treat locations as separate nests. Utility for the consumer choosing option  $h$  is written:

$$\begin{aligned} u_{hn} &= \delta_{hn} + \xi_{hn} + e_{\cdot n} + (1 - \rho)\epsilon_{hn} \\ \delta_{hn} &= x_{hn}\beta + \alpha p_{hn} \end{aligned} \tag{1}$$

where  $x$  denotes a vector of observable demand shifters,  $\xi$  is an unobserved demand shock, and  $\rho$  is a parameter reflecting correlation within the nest  $\ell$ .  $e$  and  $\epsilon$  refer to nest- and segment-level errors such that  $e_{\cdot n} + (1 - \rho)\epsilon_{hn}$  follows a Type 1 Extreme Value distribution. Hotels within each class  $h$  are aggregated and treated as homogeneous products: the price  $p_{hn}$  is observed as a quantity-weighted average of the hotel prices  $p_{jn}$  in the segment-MSA-night.

I define the market sizes  $M_n$  in each MSA following [Lewis and Zervas \(2019\)](#) and [Farronato and Fradkin \(2022\)](#), taking 2 times the maximum number of rooms sold in a given MSA. The consumer decision is independent across nights: I abstract away from any collinearity between a consumer's choice of hotel in subsequent nights. Quantities for segment  $h$  in nest  $\ell$  are thus:

$$Q_{hn}(p_{hn}, p_{\cdot n}) = M_n \cdot \frac{\exp[\delta_{hn}/(1 - \rho)]}{\exp[\delta_{\cdot n}/(1 - \rho)]} \cdot \frac{\exp[\delta_{\cdot n}]}{1 + \sum_k \exp[\delta_{kn}]} \tag{2}$$

given  $\delta_{hn} = x_{hn}\beta + \alpha p_{hn}$  and  $\delta_{\cdot n} = \sum_s \delta_{sn}$ .

The nested logit estimated equation is:

$$\log s_{hn} - \log s_{0n} = x_{hn}\beta_h + \alpha p_{hn} + \rho \log s_{hnj\cdot n} + \xi_{hn} \tag{3}$$

The linear characteristics  $x_{hn}$  contain a time trend interacted with MSA fixed effects, segment-MSA-month fixed effects to reflect the quality of different market segments across cities and their respective seasonality, and day-of-week fixed effects to capture trends within the week (such as the variation between weekday and weekend travel). I also include several weekly exogenous demand shifters: the weekly Google search rank  $G \in [0, 100]$  for “hotels [MSA]” in the prior week, the segment occupancy rate in the same week in the prior year, and the segment occupancy rate on the same day and prior day in the prior year. These variables allow for a prediction of market, segment-market, and segment-level demand shocks, and each are interacted with segment-level fixed effects in the demand specification. The parameter  $\rho$  reflects spatial differentiation across locations (nests)  $\ell \in \{\text{Downtown, Airport, Other}\}$ .

The logit demand model additionally provides for a simple closed-form expression of consumer surplus for each MSA-night  $n$ , given an unobserved constant of integration  $C$ :

$$CS_n = \frac{1}{\alpha} \log \left( 1 + \sum_s \exp \frac{\delta_{sn}}{1 - \rho} \right) A + C \quad (4)$$

My choice of demand model—and the compromises involved in aggregating away product-level variation—is based on several considerations. A major challenge in estimating hotel demand at the hotel level is the presence of capacity constraints. In markets where products are sold out – in this context, where hotels are at full capacity – the workhorse estimator of [Berry, Levinsohn, and Pakes \(1995\)](#) is misspecified as we only observe a restricted measure of demand for products, making it impossible to invert the demand system and recover correct values for  $\xi$ . Additionally, instruments constructed from rival characteristics are insufficient for identification as we do not observe the true levels of rival demand. The substitution patterns that I would recover are also incorrect. Consumers arrive to the discrete choice problem facing different choice sets as hotels go in and out of stock, and hence make different substitutions based on what products are available at different times. This added heterogeneity of choice sets provides for more complex substitution patterns than random coefficients on preferences can provide. Considering all possible choice sets is also computationally challenging: [Conlon and Mortimer \(2013\)](#) provides one such example of incorporating these aspects. Furthermore, I do not have access to the data discussed in [Agarwal and Somaini \(2022\)](#) which would be necessary for identifying latent choice sets and the probability of a consumer observing them.

There are several other solutions to the issue of identification in the presence of stockouts which are not suitable to this case. Eliminating stockout observations by aggregating instead to—for example—the hotel-week level would smooth the relationship between prices and quantities near the capacity constraint, and limit identification of the main parameters of the supply model. Alternatively, removing out-of-stock products or periods would limit variation in the instrumental variables for price, and further weaken the identification of the supply parameters.

A final concern of taking a differentiated-products approach is that my data do not provide a high degree of product differentiation. Anonymity concerns result in hotels having no attached identifying characteristics, including any finer geographic details within their MSA. This lack of spatial consideration could result in implausibly-similar substitution patterns between hotels in the same city but many miles apart compared to closer rivals. [Armona et al. \(2021\)](#) demonstrate one answer to this problem, through a search model which recovers consumer preferences using Expedia search data.

I note that there are possible improvements to the demand model that would increase the richness of consumer patterns of substitution. Additional sources of variation to better identify the coefficient on prices may enable incorporating a random-coefficients nested logit (RCNL) specification ([Brenkers and Verboven \(2006\)](#)). Separating the consumer base into finite types of leisure and business, as in [Berry and Jia \(2010\)](#), also allows for richer substitution patterns among groups with different willingness to pay and heterogeneous preferences for market segment and day of the week. Further iterations of this paper will seek to build on this.

## 4.2 Supply

Firms—indexed by  $f$ —engage in Cournot competition. Each firm chooses a vector of market-segment-level quantities  $\mathbf{Q}_f$  of rooms to sell for each night  $n$ .<sup>20</sup> The firm problem is treated as unconstrained: quantity choices are instead soft-bounded by convex, increasing costs which rise after a threshold level of occupancy  $\phi$  rather than imposing Kuhn-Tucker conditions. Firms are hence unwilling to sell rooms as they approach full occupancy with-

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<sup>20</sup>A Cournot model allows firms to have non-zero markups given the homogeneity assumption in the demand system. As hotels are homogeneous, hotel quantity decisions at the level of the firm are not meaningful, and hence I write the problem at the firm level.

out substantially higher prices. The nonlinearity between prices and occupancy rates in the hotel market is well-documented, and so the functional form of costs captures the increase in prices needed for firms to set higher quantities respective to their available room supply.<sup>21</sup> Prices are determined at the market segment level, and are shared by all firms: the inverse demand function  $p_{hn}(Q_{hn}, Q_{-hn})$  takes into account the sum of quantities per segment  $Q_{hn} = \sum_f Q_{fhn}$ .

Equation 5 shows the firm's profit-maximization function, omitting subscripts for the MSA-night as these decisions are wholly separate.

$$\Pi_f(\mathbf{Q}_f, \mathbf{Q}_{-f}) = \max_{Q_{fh}} \sum_h Q_{fh}(p_h(\mathbf{Q}_f, \mathbf{Q}_{-f})) - C_{fh}(Q_{fh}; \gamma, \phi, \eta, r) \quad (5)$$

where the key equation for cost is:

$$C_{fh}(Q_{fh}; \gamma, \phi, \eta, r) = (c_h + \gamma \log \bar{Q}_{fh} + \mu_{fh})Q_{fh} + \frac{Q_{fh}}{1 + \eta} \frac{1}{\phi \cdot \left( \sum_{j \in \mathcal{J}_{fh}} \bar{q}_j^r \right)^{1-r}} \quad (6)$$

The linear cost terms refer to segment level costs shared by all firms  $c_h$ , an unobserved cost shifter  $\mu_{fh}$ , and a term linear in log capacity  $\bar{Q}_{fh}$  which captures dispersion in costs related to firm size. The nonlinear segment of costs is governed by the soft capacity threshold  $\phi$  and the sharpness of the cost constraint  $\eta$ . These parameters are not restricted in the values they may take: Equation 6 is flexible and allows variation in the data to drive the shape of the cost function. While *a priori* I assume—and will show—this function is convex and increasing, this property of the cost function is not enforced by the modeling assumptions.<sup>22</sup>

The denominator of the cost function's nonlinear term is a CES-style aggregator of the capacities of the hotels  $j$  in firm  $f$ 's portfolio  $\mathcal{J}_{fh}$  in that segment  $h$ , where  $\sum_{j \in \mathcal{J}_{fh}} \bar{q}_j^r = \bar{Q}_{fh}$ . The efficiency parameter  $r$  captures economies of scale accrued from operating more than one hotel in the same market segment. For values of  $r < 1$  and more than one operated hotel, the aggregator's value is greater than the simple sum of capacities  $\bar{q}$ , and hence the value of the convex-and-increasing term falls at all values of  $Q$ . Hence, if the data indicate a value of  $r < 1$ , it suggests that scale tends to soften the capacity constraint.

Equation 5 produces first order conditions with marginal cost curves which are contin-

<sup>21</sup>See Kalnins et al. (2017), Cho et al. (2018), and Farronato and Fradkin (2022).

<sup>22</sup>For example, given  $\eta = 0$ ,  $C_{fh}(\cdot)$  is linear in  $Q_{fh}$ .

uous, and nonlinear after the occupancy rate  $\phi$ . I write Cournot-Nash markups  $\Omega = \Omega \cdot \frac{p}{Q}$  at the firm-segment-MSA-night level, where  $\Omega$  is a block diagonal ownership matrix.<sup>23</sup> Given that markups are estimated through the inverse demand system  $p_h(\mathbf{Q}_f, \mathbf{Q}_f)$ , the supply estimation equation is:

$$p_{hn} - \Omega_{fhn} = c_{hn} + \gamma_m \log \bar{Q}_{fhn} + \frac{Q_{fhn}}{\phi \cdot \left( \sum_{j \in J_{fn}} \bar{q}_j \right)^{1-r}} + \mu_{fhn} \quad (7)$$

I allow the parameters  $\gamma$  and  $\phi$  to vary categorically:  $\gamma$  is interacted with fixed effects at the MSA level  $m$  as different MSAs will have different inherent market sizes.  $\phi$  is interacted with nest fixed effects as different location types may have different base market tightness.

### 4.3 Identification and Estimation

The demand model faces two sources of endogeneity: prices ( $\alpha$ ), and the within-nest correlation ( $\rho$ ). Common approaches for instruments do not apply: as noted by [Armona et al. \(2021\)](#), cost shifters are not readily available. For example, many costs are contracted such that even if labor prices are observed, they do not exogenously affect prices at the frequency of the observed data. Additionally, using the within-nest number of products does not provide useful variation as the number of hotels in a market does not frequently change.

I estimate the demand system—Equation 3—using 2SLS with one instrument per endogenous regressor. The just-identified framework allows for several best-practices for weak instrument testing.<sup>24</sup>

To identify the coefficient on prices, I use a similar strategy to [Farronato and Fradkin \(2022\)](#) by exploiting the presence of capacity constraints, which are excluded from  $\delta$ . When demand is high relative to available capacity, changes in demand have a larger effect on prices: conditional on the magnitudes of the demand shifters (and hence predicted quantities demanded), market segments with fewer available rooms see higher prices: the capacity constraint acts as an excluded supply shifter. I proxy for this effect by utilizing the ratio of the exogenous variation in demand—the shifters  $x_{hn}$ —to the number of rooms in the segment  $h$ . I construct the predicted quantity  $\hat{q}$  as a function of the aforementioned demand

<sup>23</sup>Appendix B lists the full equations for elasticities and markups.

<sup>24</sup>[Andrews, Stock, and Sun \(2019\)](#).

shifters and fixed effects. Each of the continuous variables is interacted with segment-MSA-level fixed effects to add greater flexibility in the prediction, except the timetrend interacted with market-level effects.

$$z_{hn} = \frac{\hat{q}_{hn}}{\bar{q}_{hn}} \quad \text{given} \quad \log(\hat{q}_{hn}) = x_{hn}\hat{\beta}_{hn} \quad (8)$$

The identification strategy for  $\rho$  follows suggestions from [Gandhi and Houde \(2023\)](#): utilizing exogenous variation in prices. I construct a measure of the predicted price for a segment-night and use variation in the relative price of a segment to other segments in the same nest. This captures exogenous variation in the relative expensiveness of a given segment within its nest. Using the same observed characteristics and fixed effects as Equation 8, along with the price instrument interacted with product-MSA fixed effects, I estimate a predicted price variable  $\hat{p}$ , and construct the instrument for the nest share as the sum of differences between the predicted price and the predicted price of nearby rivals, using the condition of being in the same nest  $\ell$  as a discrete measure of closeness:

$$z_{sn} = \sum_{s' \in s} \hat{p}_{sn} - \hat{p}_{s'n} \quad \text{given} \quad \log(\hat{p}_{hn}) = x_{hn}\tilde{\beta}_{hn} + \tau_{hn}z_{hn} \quad (9)$$

Both instruments are then normalized to mean-zero, standard deviation 1, in order to remove differences in scaling which would impact estimation. To account for correlation in observed market data, I cluster observations at the MSA-year-month level when computing standard errors.

Estimation of markups  $\Omega = - \Omega \cdot \frac{\partial p}{\partial Q}$   $Q$  from the demand system allows for the recovery of marginal costs, and hence allows the estimation of the cost function as a nonlinear IV problem. Identification of the cost function relies on two sources of variation. The first is variation in demand shifters, which trace out the shape of the supply curve for each firm. The second is variation in firm size—both cross-sectionally and over time as ownership changes in the data—which identifies the linear cost parameter  $\gamma$  and the nonlinear efficiency parameter  $r$ .

I construct two sets of instruments. First, to define instruments for the nonlinear coefficients  $(\phi, \eta, r)$ , I follow the idea behind the construction of optimal instruments ([Chamberlain \(1987\)](#), [Reynaert and Verboven \(2014\)](#)), where instruments are the derivative of the moment condition with respect to the parameter, evaluated at the consistent estimate of the function.

Typically this is a post-estimation routine: instead, I utilize calibrated starting values for the nonlinear parameter estimates and instrument for quantities:

$$\begin{matrix} \text{h} \\ z_{fhn}, z_{fhn}, z_{fhn}^r \end{matrix} \text{ i} = E \frac{\partial \hat{\mu}_{fhn}}{\partial \theta_s} z_{fhn}^q \hat{\theta}_s, \quad (10)$$

given  $\hat{\theta}_s = (\hat{\phi}, \hat{\eta}, \hat{r}) = (0.8, 10, 0.97)$  and predicted exogenous variation in occupancy using demand shifters  $\omega_{fhn}$ .<sup>25</sup>

$$\log z_{fhn}^q = \log o\hat{c}c_{fhn} = \omega_{fhn} \hat{\lambda}_{hn} \quad (11)$$

Second, I create additional instruments to identify dispersion in costs due to firm size. Aside from the exogenous variables  $\bar{Q}_{fhn}$  interacted with MSA-level fixed effects, I include interaction terms between  $z_{fhn}$  and the number of rooms/hotels owned by firm  $f$  in segment-night  $hn$ . As firm size effectively shifts the capacity threshold  $\phi$  through the nonlinear parameter  $r$ , this interaction of firm size and the identifying variation for  $\phi$  improves identification for  $r$ .

Using the full set of instruments  $Z_{fhn}^S$  I construct the set of moments  $m(\theta^S)$  and minimize the objective function  $q(\theta^S)$  using a 2-step approach:

$$\begin{aligned} m(\theta^S) &= \times \mu_{fhn} \cdot Z_{fhn}^S \\ q(\theta^S) &= m(\theta^S)' W m(\theta^S) \end{aligned} \quad (12)$$

where  $W$  is an initial weight matrix configured for MSA-year-month clustering.

## 5 Results

In this section, I report parameter estimates for the demand and supply models, as well as the recovered markups and marginal costs from the model estimates. Additionally, I present a simplified representation of upward pricing pressure to place the parameter estimates in an applied context.

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<sup>25</sup>These are the same demand shifters as in the demand system, but taken at the firm level rather than the segment level.

## 5.1 Demand Parameter Estimates

Table 5 presents the estimated coefficients of the nested logit demand model. The key parameters ( $\alpha, \rho$ ) are statistically-significant at the 1% level. Specification (1) is presented primarily to validate the instrument for price using the best practices of a one-regressor, one-instrument specification. For this, I present test results for weak-instrument detection suited to non-homoskedastic standard errors, which suggest I can reject the issue of weak instruments (the effective F statistic of [Montiel and Pfluenger \(2013\)](#) for  $k = 1$  and the [Kleibergen and Paap \(2006\)](#) robust F statistic for  $k = 2$ ). Appendix C includes the results of further instrument tests.

My estimated elasticities for Specification (2) by quality class range from  $-6.10$  for luxury hotels to  $-1.71$  for economy hotels. Comparing my estimates for Austin, TX to literature values, I find a range of  $-5.70$  for luxury to  $-1.84$  for economy versus  $-7.49$  to  $-1.59$  by [Farronato and Fradkin \(2022\)](#). However, the comparison values incorporate a more complex specification with variation in price preference, and a different product space.<sup>26</sup> Own-price elasticities also vary intuitively by location: airport hotels face less price-sensitive demand with own-price elasticity of  $-2.26$  compared to urban hotels with  $-3.47$ . Appendix D contains more details on estimated elasticities.

Table 5: Estimated Demand Coefficients

	(1)		(2)	
Price	0.037	(0.005)	0.014	(0.001)
log Nest Share	-	-	0.548	(0.075)
Number of Observations	191,648		191,648	
Specification	Logit		Nested Logit	
Median Own-Price Elasticity	3.38		2.49	
Estimator	2SLS		2SLS	
Excluded Instruments	$Z_{hn}$		$Z_{hn}; Z_{hn}$	
F Statistic	153.0		36.9	

The coefficients are excluded for brevity. Estimation sample includes daily category-level observations from 15 MSAs from 2015-2017. All specifications include fixed effects at the segment-MSA-month and day-of-week levels. Standard errors are clustered at the MSA-year-month level. Specification (1) reports the Montiel-Pfluenger Effective F statistic, while Specification (2) reports the Kleibergen-Paap Robust F statistic.

<sup>26</sup>I note that while [Farronato and Fradkin \(2022\)](#) estimate random coefficients on both the constant and price, neither estimate of standard deviation is statistically significant.



## 5.2 Recovered Costs

In Table 6, I summarize the recovered markups and costs. The values pass a useful sanity check: segment-level prices and mean segment-level costs are monotonic in quality. However, a subset of observations are outliers: high-cost and low-quantity San Antonio luxury hotels recover extremely high markups and hence disproportionately low costs in those periods. I also include the distribution of price-cost margins  $\frac{p_{hn} - c_{fhn}}{p_{hn}}$  in Appendix Figure 6. As markups are computed at the firm level, they are lower than the segment-level elasticities might imply.<sup>27</sup>

Table 6: Summary of Recovered Markups and Costs

	N	Prices		Markups		Marginal Costs	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Luxury	34,404	215.2	57.8	20.4	15.6	194.8	59.9
Upper Upscale	136,007	146.0	39.0	14.1	12.1	131.9	41.4
Upscale	120,625	115.9	27.3	17.6	11.5	98.4	29.0
Upper Midscale	164,163	98.6	23.9	14.0	11.5	84.7	25.1
Midscale	102,194	73.3	17.5	17.6	18.1	55.6	25.2
Economy	123,630	59.3	15.0	13.9	11.0	45.4	17.1

While costs (and hence markups) are partially an abstraction in this context, they can be compared to data as a sanity check, and to gauge whether I am over-estimating markups. The nested logit specification obtains more inelastic estimates than other literature values. Additionally, the Cournot-Nash supply specification produces higher markups than an equivalent Bertrand model (Magnolfi, Quint, Sullivan, and Waldfogel (2022)). On the other hand, data from the STR Global Hotel Profitability Review for US Midscale/Economy Hotels—where revenue per occupied room is almost entirely ADR and hence there are few confounding revenue channels—reports mean EBITDA of \$32.33 on ADR of \$80.41 (40.2%). I do not have estimates for the non-included fixed expenses and non-operating expenses, but as a preliminary point this suggests my estimates for markups (\$17.60, or 25.2% for Midscale hotels) are not dramatically overstated.

<sup>27</sup>  $j \frac{\partial Q_h}{\partial p_h} \frac{p_h}{Q_h} > j \frac{\partial Q_h}{\partial p_h} \frac{p_h}{Q_{fh}}$  if  $Q_h > Q_{fh}$ . Hence, firm-level elasticities are higher in magnitude than segment-level elasticities, and this greater elasticity results in lower markups at the firm level.

### 5.3 Supply Parameter Estimates

Table 7 summarizes the supply specification coefficient results. I estimate a threshold parameter of 0.67 to 0.76. This is lower than values in the literature (Kalnins et al. (2017) cites a range of 80% to 85% while Farronato and Fradkin (2022) use values of 0.85), though this can be explained by the difference in functional form. Urban hotels are the most tightly capacity-constrained, while airport hotels are the least. All parameters are statistically significant at the 1% level. The linear cost parameters on the log number of rooms ( $\gamma_m$ ) are omitted from the table, but are statistically significant and less than zero in all cases. Furthermore, I am able to reject the hypothesis that scale is irrelevant to the nonlinear capacity constraint ( $r = 1$ ).

Table 7: Estimated Supply Model Coefficients

Parameter	Category	(1)	
Threshold	Airport	0.764	(0.023)
	Urban	0.667	(0.026)
	Other	0.732	(0.021)
Sharpness		9.996	(0.943)
Efficiency	r	0.981	(0.003)
Observations	N	679,578	

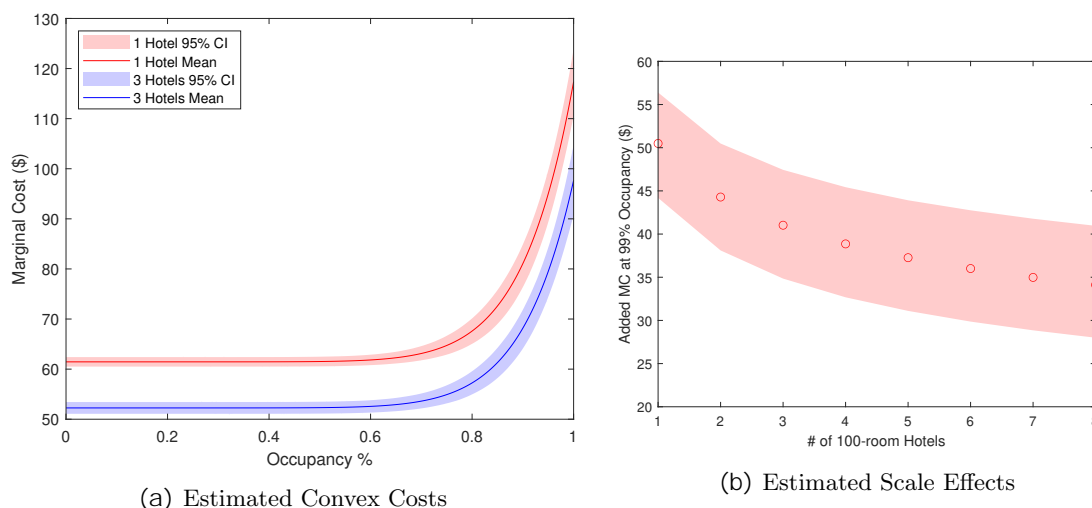
Specification contains segment-MSA, year-month, and day-of-week fixed effects. Standard errors are clustered at the level of MSA-month-year.

These results are simpler to parse visually: Figure 6 displays bootstrapped confidence intervals on two aspects of the estimated coefficients. Panel A shows the added convex marginal costs as a function of occupancy for a firm with 1 or 3 identical hotels and a base  $c_h = 100$ . As occupancy rates approach 100%, marginal costs rise by approximately \$50 to \$60. The difference in marginal cost between the two rises from \$9.20 to \$19.67 as the nonlinear costs for the firm with  $n(\mathcal{J}) = 3$  are less steep. As such, a merger of independent firms stands to have noticeable reductions in costs.

Panel B visualizes the impact of the efficiency parameter through the added nonlinear marginal costs at an occupancy rate of 99% for firms operating  $\{0, 8\}$  identical hotels: the y-axis demonstrates the difference between the marginal costs at high occupancy versus low occupancy. The cost-reduction effects are most pronounced at lower values: the acquisition of independent or isolated hotels has a larger effect than the merger of two large overlapping chains. Costs fall from \$52 for an independent firm to under \$40 once the firm holds  $n(\mathcal{J}) >$

3. The implication of this result varies based on the type of merger. First, a merger of two smaller or independent firms stands to reduce costs at the constraint for both the acquirer’s and targets’s capacities. On the other hand, larger chains have already internalized much of the potential efficiency with respect to the capacity constraint and allocating quantities, mergers will have limited subsequent effects on this channel of efficiency, though when acquiring smaller rivals the average cost on the acquired capacities will still fall. As larger firms are the primary entity of interest when regulating mergers, the efficiency argument should be assessed in this light.

Figure 6: Bootstrapped Estimated Functions



## 5.4 Upward Pricing Pressure Example

To better visualize the relative magnitudes of the markup and cost efficiency changes, I construct a simulated environment using the estimated model. The market contains 16 homogeneous hotels engaging in Cournot competition. All hotels are located in the same nest, with the outside option being contained in a separate nest. Firm  $F_i$  owns  $\{1, \dots, 8\}$  hotels, and acquires  $\{1, \dots, 8\}$  of the remainder. All other hotels are owned independently by firms  $F_{-i}$ . This creates 64 merger scenarios, where the initial concentration and size of the acquisition are varied. In the initial state, all hotels—which have 100 rooms—sell 99 rooms and are at the edge of being out of stock. The results of this exercise can be read as the comparative heights of the price and marginal cost curve across a range of firm concentrations.

The unilateral effect is estimated as the net change in markups and costs, holding per-hotel quantities constant. Firm quantity  $Q_i = 99 \times n(F_i)$ : 99 rooms times the number of owned hotels (and hence  $Q_i^\theta$  is the new firm-level sum equal to  $n(F_i^\theta) \times 99$ ):

$$\Delta(p)_i = \underbrace{-\frac{\partial p}{\partial Q_i^\theta} Q_i^\theta + \frac{\partial p}{\partial Q_i} Q_i}_{\text{Change in Markups}} + \underbrace{(C_i(Q_i^\theta) - C_i(Q_i))}_{\text{Change in Costs}} \quad (13)$$

This approach does not define an equilibrium: it would be expected that rising markups in the merged body results in reduced quantities. However, it provides an initial screen for the expected price effects of a merger: [Miller et al. \(2017\)](#) discuss how unilateral effects may be valuable—if not accurate—in determining merger outcomes. A positive effect would suggest, *ceteris paribus*, that the merged firm would reduce quantities and prices would respond upwards.

Figure 7: Estimated Unilateral Change in Prices (%)



Figure 7 displays the results, showing that only in the smallest merger environments—those of 2-3 independent firms merging—do the cost efficiencies wholly outweigh changes in markups. In larger mergers the efficiencies are present but insufficient to outweigh the unilateral effects of the merger in driving prices higher.

## 6 Counterfactual Analysis

In this section, I conduct two types of merger simulations in order to test the magnitudes of merger-specific efficiencies, markups, and welfare effects. First, I simulate a universe of hypothetical mergers to display trends in the net welfare effects with respect to the change in market concentration. Second, to provide external validity, I construct two bilateral mergers in the data: a pair of large firms, and a large firm and an independent hotel. The former would fall at the threshold of the agencies’ current structural presumptions and be a candidate—though not a guaranteed case—for regulation. The latter merger would likely not face immediate regulatory attention, but a sequence of such acquisitions over time might still have detrimental consumer effects in its entirety (Wollman (2021)) and reflect a limitation in presumptive screening.<sup>28</sup>

Future work in this section will aim to construct alternative policy-relevant merger scenarios: mergers among small firms which may be consumer-beneficial, and sequential acquisitions of small firms by a single large firm.

### 6.1 Policy Experiment

What is the general net effect of mergers which achieve merger-specific efficiencies but also allow for anti-competitive effects? This policy experiment provides evidence by simulating a range of firm sizes in a test market, and examining permutations of bilateral mergers. I use the estimated demand and supply model parameters to calibrate the simulation.

The test market contains four market segments placed in two nests, with 10 firms who vary in the number of rooms, properties, and the segments in which they operate. The base market has a HHI of 1,409, which results in any merger which increases HHI by at least 100 satisfying the 2010 guidelines’ structural presumption of a merger in a “moderately concentrated” market.<sup>29</sup> Over 100 simulated days, the market has average occupancy of approximately 80%: these high-demand periods increase the importance of scale economies with respect to capacity constraints.

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<sup>28</sup>The Draft Merger Guidelines Guideline 9 specifically notes that the Agencies may examine the full series of acquisitions as a whole.

<sup>29</sup>The Draft Merger Guidelines adjust this threshold to 1,800 but dispense with the various ranges of concentration.

The mergers throughout this section are simulated in typical fashion by updating the ownership structure in Equation 7 and finding the equilibrium fixed point (Nevo (2000)), with one distinction: the product space itself potentially changes as the equilibrium is defined at the firm-segment level. When two firms overlap in a segment, the post-merger environment contains one observation with their joint capacities, which affects  $\bar{Q}$  and the denominator of the marginal cost function. Additionally, the new (presumably larger) single firm-segment quantity choice affects the computation of markups as the joint firm has more impact in choosing segment-level quantities and hence defining prices in that segment.

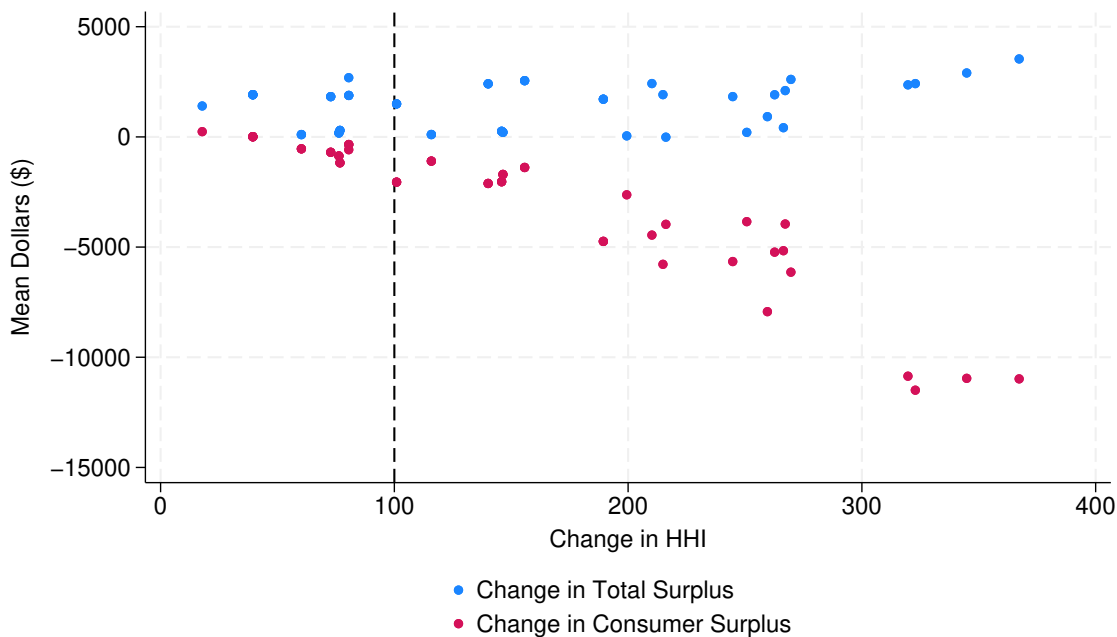
Figure 8 displays the mean welfare effects of each of these 45 bilateral mergers. Mergers below the threshold of harm ( $\Delta_{HHI} < 100$ ) are minimally harmful to consumers or even beneficial - these represent mergers among independent hotels. Overall, consumer surplus falls in all but the smallest of cases, and this reduction increases with the increase of market concentration. Both the size and breadth (number of operated segments) of firms matters: efficiencies are not earned through mergers of non-overlapping hotels, but these can still raise markups. A final observation is that mergers generally increase *total* surplus as a result of earned efficiencies, but these are not passed through to consumers in light of increased markups. These efficiencies are—in cases where firms have substantial segment overlap—reflected in changes in occupancy rates (see Appendix Figure 7).

The result that larger mergers result in worse consumer welfare outcomes—despite gains in total surplus from efficiencies that are not passed through—is also reflected in less concentrated markets. Appendix Figure 8 repeats this policy experiment using 16 firms and an initial HHI of 824, and obtains the same pattern of outcomes.

## 6.2 Merger Analysis

To compare the test markets to real data, I simulate two bilateral mergers of parent companies in Madison, Wisconsin. The chosen firms are anonymous. The first merger reflects a case inviting structural presumption: both firms operate large national chains. The second is a case of a acquisition of an independent hotel by one of these major chains, representative of a small step in a potential sequence of consolidation. I focus on the local market of Madison in 2017 rather than any regional or national-level effects. An important consideration is whether these mergers are sufficiently in-sample: without knowing the identities of the firms, it is possible that—particularly in the first case—these mergers would simply not

Figure 8: Policy Experiment Results (Welfare)



fit the type of variation present in the data. However, the merger of large chains (Marriott-Starwood, Wyndham-La Quinta, and the recently proposed-but-rejected Choice-Wyndham) is not overly unrealistic and the estimation sample includes the Marriott-Starwood event.

Table 8 displays the distribution of hotel and mean quantities sold in 2017 for the two merging firms and the rest of the market. The merging parties have substantial overlap in the Upscale and Upper Midscale segments of the non-Airport/Urban locations. The total MSA (“Other” location) HHI is 1,176 (1,675) and would rise to 1,548 (2,423) with pre-merger quantities - as a merger of large parent companies, there are substantial increases in market concentration. From the policy experiment and what one would expect of mergers, this case is one that would be assumed to be consumer harmful ex ante, and hence addresses the question of whether the existing presumptive screens are able to reject mergers appropriately in the sector.

The similarity in size of the two firms results in similarities in their pre-merger costs and occupancy rates. Appendix Figure 9 shows via a binned scatterplot of marginal costs on occupancy that the recovered cost curves of the two firms largely overlap. Additionally,

Appendix Figure 10 demonstrates that the distribution of occupancy rates between the two firms is fairly similar, with one of the two firms having more density at 80% occupancy rates.

Table 8: Counterfactual Merger Scenario (Large Firms)

		Firm 1		Firm 2		Other	
		Hotels	Quantity	Hotels	Quantity	Hotels	Quantity
Urban	Luxury					2	462
	Upper Upscale					2	209
	Upscale					4	509
	Upper Midscale					3	366
Other	Upper Upscale			2	273		
	Upscale	3	274	4	243	5	395
	Upper Midscale	6	421	3	207	13	788
	Midscale	1	77			13	600
	Economy					14	512

Values shown are the number of owned hotels and mean number of rooms sold across owned hotels.

The second merger scenario’s setup is displayed in Table 9: Firm 2 is kept the same, but its merging party (the new “Firm 1”) is an independent Upper Midscale hotel. The HHI increase in pre-merger quantities is modest to the point of being de minimis: from 1,176 in the same pre-merger case to 1,205. Alternatively, if the market definition was narrowed to the “Other” location category, this shift in HHI would be from 1,675 to 1,734. At the MSA level, this is well under any presumptive screen, while a tighter market definition suggests moderate concentration but a small (sub-100) increase resulting from the merger. However, this case could be considered as a single step in a series of acquisitions that build a given firm into a larger local or regional chain. Regulators may consider in whole a series of such mergers which collectively drive larger increases in concentration.

As in the prior case, I compare the cost structure and occupancy rates of the two merging firms. The disparate sizes of the two firms lead to more heterogeneity: Appendix Figure 11 demonstrates that the smaller of the two firms (denoted “F1”) has substantially more scattered and generally higher recovered marginal costs (i.e. lower scale, and a higher dispersion of  $\mu$ ). This is also reflected in the distribution of occupancy rates for this firm (denoted by  $firm\_ids = 16$ ) in Appendix Figure 12, which are much more dispersed than the larger firm’s. As such, one can expect ex ante that the merger will result in substantial cost decreases and higher capacity utilization for the capacity that is to be acquired, though it is a relatively small quantity. This example extends more generally to cases where there



Table 9: Counterfactual Merger Scenario (Small Acquisition)

		Firm 1		Firm 2		Other	
		Hotels	Quantity	Hotels	Quantity	Hotels	Quantity
Urban	Luxury					2	462
	Upper Upscale					2	209
	Upscale					4	509
	Upper Midscale					3	366
Other	Upper Upscale			2	273		
	Upscale			4	243	8	669
	Upper Midscale	1	58	3	207	18	1151
	Midscale					13	638
	Economy					14	512

Values shown are the number of owned hotels and mean number of rooms sold across owned hotels.

is substantial variation in the unobserved cost shock  $\mu$  across firms: averaging out these cost shocks in the joint firm serves to bring down costs where they are highest, and raise occupancy. The variation in  $\mu$  is observable by proxy by looking at correlation between capacity utilization rates.

Table 10 presents the results of the mergers, broken out by merging and non-merging parties and presenting a set of capacity-weighted averages. In the first (the larger) merger, the merging firms decrease their occupancy rates ( $-6.9\%$ ) owing to substantially higher markups, despite decreases in both marginal and average costs. The markup effect—firms reducing quantities to earn monopolistic profits—hence dominates the efficiency effect, and the result of this is that prices in segments where the merging firm operates rise. Conversely, as non-merging firms respond to the consolidation, they raise their own occupancy rates which results in turn in higher marginal and average costs. These impacts are shown in Appendix Figure 13, which displays a binned scatterplot of the marginal costs on occupancy for the merging firms before and after the merger. The efficiencies provide a minor offset: prices in segments where the merging firms operate rise, but rise by less than when considering the set of all segments (as non-merging firms operate across the entire market).

The second (smaller) merger shows the opposite result. The small acquisition does not provide for much increase in market power, but it does cut costs - primarily on the set of acquired rooms. The result is that merging firms raise their occupancy rate ( $8.9\%$ ) as they more efficiently utilize capacity, which leads to falling prices in the segments where

the merged firm operates.<sup>30</sup> In this case, the efficiency effect—where lower costs result in higher equilibrium quantities— dominates. Marginal costs rise in this case, driven by higher capacity utilization. The shift in the cost curve for merging firms is shown in Appendix Figure 14. The change in the cost curve values is less pronounced than in the first merger, but there are more observations along the convex element of the curve as the smaller increase in markups does less to inhibit the merged firm from choosing higher quantities (and hence occupancy rates). Non-merging firms in turn are largely unaffected, as the magnitude of the merger is small overall.

Table 10: Firm-level Merger Effects

	Merging Firms				Non-Merging Firms			
	Merger 1		Merger 2		Merger 1		Merger 2	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Occupancy	65%	60%	66%	72%	65%	67%	65%	65%
Price	\$ 115.21	\$ 117.12	\$ 118.34	\$ 116.42	\$ 115.90	\$ 118.33	\$ 115.26	\$ 117.08
Markups	\$ 27.40	\$ 40.54	\$ 32.97	\$ 30.90	\$ 19.15	\$ 21.13	\$ 19.47	\$ 21.11
Marg. Cost	\$ 87.81	\$ 76.50	\$ 85.38	\$ 85.50	\$ 96.75	\$ 97.18	\$ 95.79	\$ 95.95
Avg. Cost	\$ 85.33	\$ 74.50	\$ 82.31	\$ 79.99	\$ 89.53	\$ 89.57	\$ 89.40	\$ 89.41

To assess welfare, I look at the market-level: results for both mergers are presented in Table 11. As suggested by the policy experiment, a merger of two larger chains (Merger 1) has a negative effect on consumer surplus as prices rise (−1.98%). There are modest decreases in average costs (−3.54%), driven in part by cost reduction in the merging firm as well as quantity reductions for the merging firm, as it reduces its capacity utilization. The effects on consumers are partially offset by the efficiencies: consumers face a drop in approximately \$1.2 million in consumer surplus over the course of a year. Additionally, the presence of efficiencies is noted through the slight positive impact on total surplus, driven by substantial increases in profits. Owing to the non-merging firm response to the merger, mean daily quantities rise.

In the case of the smaller acquisition (Merger 2), the effect on quantities is positive and larger (1.12%), as prices increase to a smaller degree across all segments. The effects on costs and markups are also smaller in magnitude owing to the smaller size of the merger. Profits and total surplus rise by a smaller amount than the first merger. More importantly, consumer surplus is non-negative, with an extremely marginal increase (0.10%), suggesting

<sup>30</sup>Kalnins et al. (2017) discuss in more theoretical detail the reasons why mergers may increase output in the lodging industry with respect to the management of the firms' capacity constraints.

that the earned efficiencies wholly offset the anti-competitive effects of the merger. This fits the policy experiment where smaller mergers (in terms of increased concentration) had smaller effects on both total and consumer surplus, but additionally suggests an example of a case where the effect on consumers is positive.

Table 11: Market-level Merger Effects

	Pre-Merger	Merger 1		Merger 2	
Daily Quantity	5,296	5,304	0.16%	5,355	1.12%
Price	\$ 122.83	\$ 124.91	1.70%	\$ 123.99	0.94%
Avg. Cost	\$ 91.38	\$ 88.14	-3.54%	\$ 90.41	-1.05%
Markups	\$ 22.80	\$ 27.85	22.19%	\$ 24.24	6.35%
Consumer Surplus	60.2m	59.0m	-1.98%	60.3m	0.10%
Profit	60.8m	71.2m	17.09%	65.6m	7.93%
Total Surplus	121.0m	130.2m	7.60%	125.9m	4.04%

There are several extensions to this analysis that I aim to pursue in future versions. First, the analysis thus far is able to affirm that the structural presumption is—at least in part—reasonable in the hotel sector. The screen would reject the larger chain merger where efficiencies are not passed through in magnitudes sufficient to offset markups, and it would pass the smaller acquisition where anti-competitive effects are offset. Next, I aim to provide evidence for at what point a series of acquisitions becomes anti-competitive at the margin or when taken as a whole. Second, I aim to parse these results into a more granular form. For example, assessing whether these results are equivalent across weekday and weekend guests, or have seasonal variance in their results, in order to consider if losses are specifically concentrated. Third, I hope to expand understanding of the implications of the supply model’s parameter estimates by finding what value(s) of  $r$  would be necessary to drive pro-competitive outcomes from mergers.

### 6.3 Policy Implications

The counterfactual experiments demonstrate that efficiencies in the hotel sector are measurable and may improve welfare and utilization, but are unlikely to offset increases in markups in all but the smallest of mergers where the increase in concentration applies negligible upwards pressure on prices. A structural presumption based on  $\Delta$ HHI is sufficient to identify mergers which are anti-competitive and lead to welfare losses. Furthermore, this suggests that consolidation in the sector is generally harmful for consumers, and efficiencies

should not be considered a sufficient defense when the merger meaningfully affects market concentration.

The sequential pattern of acquisitions among major firms which develop larger portfolios in small steps—as the Draft Merger Guidelines discuss—may also be worth deeper consideration. Small mergers with dispersion in costs may fall under regulatory thresholds and may be pro-competitive, but taken as a whole these serial consolidations are likely to be anti-competitive in the long run as the total size of the firm grows. As such, regulators should increase scrutiny of these acquisitions, particularly focusing on determining what point these become anti-competitive, as the evidence suggests a non-monotonic pattern of consumer welfare outcomes across the sequence. This includes cases where they are undertaken by management firms, real estate investment trusts, or equity funds who hold properties and brand lines, rather than hotel parent companies.

A topic that this paper does not address is whether these results hold equivalently for chain-managed versus franchised hotels. It is conceivable that franchised hotels do not operate to jointly profit-maximize with potentially-rival other franchisers under the same corporate banner. This would constrain the ability of firms to earn higher markups, but also diminish efficiencies suggested by the value of recapturing spillover demand (as franchisers do not value demand captured by co-branded rivals). Future versions of this paper will aim to incorporate this element. Furthermore, the counterfactual does not consider the potential for affecting entry: [Farrell and Shapiro \(2018\)](#) note that, in general, the potential entrant defense is seen skeptically in the context of horizontal mergers.

## 7 Conclusion

This paper studies the impact of capacity constraints on competition, recovering the shape of the soft capacity constraint and estimating how it varies based on firm size. I use these estimates to explore the issue of estimating the relative impact of merger-specific efficiencies in the scenario of hotel chain mergers as a pro-competitive offset to market concentration. The importance of this analysis is evident in light of continued consolidation of the US hotel sector through both large, visible mergers and smaller brand and property acquisitions, and the Agencies' current updating of the Merger Guidelines.

Using data which contains variation in nightly demand for various hotel market segments

and variation in firm supply—quantities of rooms and hotels—I present and estimate a model of demand and supply in the US hotel sector. I find that owning multiple properties within the same market segment decreases firm costs: first, the marginal cost of selling a given room falls in the number of owned rooms, and second, by reducing the degree to which the firm’s capacity constraint drives higher costs. I show that the presence of the capacity constraint raises marginal costs—here the minimum price acceptable to firms—by over \$50 for a firm with a single property. This value decreases to \$40 for a firm with 4 properties in the same market segment.

My analysis suggests that merger-specific efficiencies are not sufficiently passed through to consumers to result in the majority of mergers being pro-competitive. The exceptions are small acquisitions with minimal effects on market concentration, where the gain to consumer welfare is accordingly small. Efficiency gains are captured largely as increased profit by merged firms, and while price increases are partially offset, unilateral effects suggest upward pricing pressure in all but the smallest combinations of firms. In a simulated policy experiment of bilateral mergers, consumer surplus falls in the degree of increased market concentration, while total surplus remains slightly positive. I then construct two relevant examples of chain mergers—between two chains, and between a chain and an independent—in real data and find that the large merger would harm consumers while the small has a slight positive impact. The mergers result a loss of approximately \$1.2 million (-2.0%) when chains merge despite falling average costs, and a gain of \$0.1 million (0.1%) when a chain acquires an independent firm. Rising profits due to markups and efficiencies result in increases in total surplus of \$10.2 million (7.6%) and \$4.9 million (4.0%) respectively, over the course of one year.

This paper leaves open several avenues for future research. For example, should we reject the assumption that franchisees operate with the same conduct as chain-managed hotels within the same firm? A conduct-testing approach (e.g. [Duarte, Magnolfi, Sølvesten, and Sullivan \(2022\)](#)) would enable study of whether the trend of divesting hotels to franchises would have a diminishing effect on markups, and hence expand regulatory understanding of the net effect of mergers given this trend. In order to do so, additional approaches to computing hotel-level substitution patterns and therefore hotel-level markups may be necessary.

## References

- Agarwal, N. and P. J. Somaini (2022): “Demand Analysis under Latent Choice Constraints,” Working Paper 29993, National Bureau of Economic Research.
- Aguirregabiria, V. and J. Jeon (2020): “Firms’ Beliefs and Learning: Models, Identification, and Empirical Evidence,” *Review of Industrial Organization*, 56, 203–235.
- Aguirregabiria, V. and A. Magesan (2020): “Identification and Estimation of Dynamic Games When Players’s Beliefs Are Not in Equilibrium,” *The Review of Economic Studies*, 87, 582–625.
- Andrews, I., J. Stock, and L. Sun (2019): “Weak Instruments in IV Regression: Theory and Practice,” *Annual Review of Economics*, 11, 727–753.
- Armona, L., G. Lewis, and G. Zervas (2021): “Learning Product Characteristics and Consumer Preferences from Search Data,” in *Proceedings of the 22nd ACM Conference on Economics and Computation*, 98–99.
- Ashenfelter, O. C., D. S. Hosken, and M. C. Weinberg (2013): “The Price Effects of a Large Merger of Manufacturers: A Case Study of Maytag-Whirlpool,” *American Economic Journal: Economic Policy*, 5, 239–261.
- Berry, S. and P. Jia (2010): “Tracing the Woes: An Empirical Analysis of the Airline Industry,” *American Economic Journal: Microeconomics*, 2, 1–43.
- Berry, S., J. Levinsohn, and A. Pakes (1995): “Automobile prices in market equilibrium,” *Econometrica*, 841–890.
- Besanko, D. and U. Doraszelski (2004): “Capacity Dynamics and Endogenous Asymmetries in Firm Size,” *The RAND Journal of Economics*, 35, 23–49.
- Bhattacharya, V., G. Illanes, and D. Stillerman (2023): “Merger Effects and Antitrust Enforcement: Evidence from US Retail,” Working Paper 31123, National Bureau of Economic Research.
- Brenkers, R. and F. Verboven (2006): “Liberalizing a Distribution System: The European Car Market,” *Journal of the European Economic Association*, 4, 216–251.
- Carlton, D. (2009): “The Need to Measure the Effect of Merger Policy and How to Do It,” *Competition Policy International*, 5.

- Chamberlain, G. (1987): “Asymptotic Efficiency in Estimation with Conditional Moment Restrictions,” *Journal of Econometrics*, 34, 305–334.
- Cho, S., G. Lee, J. Rust, and M. Yu (2018): “Optimal Dynamic Hotel Pricing,” *Working Paper*.
- Conlon, C. and J. Mortimer (2013): “Demand Estimation under Incomplete Product Availability,” *American Economic Journal: Microeconomics*, 5, 1–30.
- Dogru, T., A. Erdogan, and M. Kizildag (2018): “Marriott Starwood merger: what did we learn from a financial standpoint?” *Journal of Hospitality and Tourism Insights*, 1, 121–136.
- Duarte, M., L. Magnolfi, M. Sivsten, and C. Sullivan (2022): “Testing Firm Conduct,” *Working Paper*.
- Farrell, J. and C. Shapiro (2018): “The 2010 Horizontal Merger Guidelines After 10 Years,” *Review of Industrial Organization*, 58, 1–11.
- Farronato, C. and A. Fradkin (2022): “The Welfare Effects of Peer Entry in the Accommodation Market: The Case of Airbnb,” *American Economic Review*, 112, 1782–1817.
- Fowlie, M., M. Reguant, and S. P. Ryan (2016): “Market-based emissions regulation and industry dynamics,” *Journal of Political Economy*, 124, 249–302.
- Gandhi, A. and J.-F. Houde (2023): “Measuring Substitution Patterns in Differentiated-Products Industries,” *Working Paper*.
- Gandhi, A. and A. Nevo (2021): “Empirical Models of Demand and Supply in Differentiated Products Industries,” *Handbook of Industrial Organization*, 4, 63–139.
- Gedge, C., J. W. Roberts, and A. Sweeting (2020): “A Model of Dynamic Limit Pricing with an Application to the Airline Industry,” *Journal of Political Economy*, 128, 1148–1193.
- Goettler, R. L. and B. R. Gordon (2011): “Does AMD Spur Intel to Innovate More?” *Journal of Political Economy*, 119, 1141–1200.
- Hollenbeck, B. (2017): “The Economic Advantages of Chain Organization,” *The RAND Journal of Economics*, 48, 1103–1135.

- Kalnins, A. (2006): “Markets: The U.S. Lodging Industry,” *Journal of Economic Perspectives*, 20, 203–218.
- Kalnins, A., L. Froeb, and S. Tschantz (2017): “Can mergers increase output? Evidence from the lodging industry,” *RAND Journal of Economics*, 48, 178–202.
- Kimes, S. E. (1989): “Yield Management: A Tool for Capacity-Constrained Service Firms,” *Journal of Operations Management*, 8, 348–363.
- (2017): “The Future of Hotel Revenue Management,” Tech. Rep. 1, Cornell Center for Hospitality Research.
- Kleibergen, F. and R. Paap (2006): “Generalized Reduced Rank Tests using the Singular Value Decomposition,” *Journal of Econometrics*, 133, 97–126.
- Kosova, R., F. Lafontaine, and R. Perrigot (2013): “Organizational Form and Performance: Evidence from the Hotel Industry,” *The Review of Economics and Statistics*, 95, 1303–1323.
- Kwoka, J. E. (2014): *Mergers, Merger Control, and Remedies: A Retrospective Analysis of US Policy*, MIT Press.
- (2016): “The Structural Presumption and the Safe Harbor in Merger Review: False Positives or Unwarranted Concerns,” *Antitrust Law Journal*, 81.
- Kwoka, J. E. and L. J. White (1999): *The Antitrust Revolution: Economics, Competition, and Policy*, Oxford University Press.
- Law, R., S. Lee, Q. Xiao, and F. Zhang (2020): “Mergers and Acquisitions in the Hotel Industry: a Comprehensive Review,” *International Journal of Hospitality Management*, 91.
- Lewis, G. and G. Zervas (2019): “The Supply and Demand Effects of Review Platforms,” *Working Paper*.
- Magnoli, L., D. Quint, C. Sullivan, and S. Waldfogel (2022): “Differentiated-products Cournot Attributes Higher Markups than Bertrand-Nash,” *Economics Letters*, 219.
- Mazzeo, M. J. (2002): “Product Choice and Oligopoly Market Structure,” *The RAND Journal of Economics*, 33, 221–242.



- McGill, J. I. and G. J. Van Ryzin (1999): “Revenue Management: Research Overview and Prospects,” *Transportation Science*, 33, 233–256.
- Miller, N. H., M. Remer, C. Ryan, and G. Sheu (2017): “Upward Pricing Pressure as a Predictor of Merger Price Effects,” *International Journal of Industrial Organization*, 52, 216–247.
- Montiel, J. L. and C. E. Pflueger (2013): “A Robust Test for Weak Instruments,” *Journal of Business and Economic Statistics*, 31, 358–369.
- Nevo, A. (2000): “Mergers with Differentiated Products: The Case of the Ready-to-Eat Cereal Industry,” *The RAND Journal of Economics*, 31, 395–421.
- Nocke, V. and M. D. Whinston (2022): “Concentration Thresholds for Horizontal Mergers,” *American Economic Review*, 112, 1915–1948.
- Reynaert, M. and F. Verboven (2014): “Improving the performance of random coefficients demand models: the role of optimal instruments,” *Journal of Econometrics*, 179, 83–98.
- Roper, A. (2018): *Vertical Disintegration in the Corporate Hotel Industry*, Routledge Research in Hospitality.
- Rose, N. L. and C. Shapiro (2022): “What Next for the Horizontal Merger Guidelines,” *Antitrust*, 36, 4–13.
- Ryan, S. P. (2012): “The Costs of Environmental Regulation in a Concentrated Industry,” *Econometrica*, 80, 1019–1061.
- Scott Morton, F. M. (2019): “Modern U.S. Antitrust Theory and Evidence Amid Rising Concerns of Market Power and its Effects: An Overview of Recent Academic Literature,” Tech. rep., Center for Equitable Growth.
- Shapiro, C. (2021): “Antitrust: What Went Wrong and How to Fix it,” *Antitrust*, 35, 33–45.
- U.S. Department of Justice and Federal Trade Commission (2010): “Horizontal Merger Guidelines,” .
- (2023): “Draft Merger Guidelines,” .

Whinston, M. D. (2007): “Antitrust Policy Towards Horizontal Mergers,” *Handbook of Industrial Organization*, 3, 2369–2440.

Williams, K. R. (2022): “The Welfare Effects of Dynamic Pricing: Evidence from Airline Markets,” *Econometrica*, 90, 831–858.

Williamson, O. E. (1968): “Economies as an Antitrust Defense: The Welfare Tradeoffs,” *American Economic Review*, 58, 18–36.

Wolman, T. G. (2021): “How to Get Away with Merger: Stealth Consolidation and its Effects on US Healthcare,” Working Paper 27274, National Bureau of Economic Research.

## Appendix A Equivalence of Nonlinear Pricing and Convex Costs

In this section, I demonstrate that a model of simple conduct and convex marginal costs recovers the outcomes of constrained nonlinear pricing behavior. The goal is to show that a model of a price-setting hotel, given (a) demand uncertainty and (b) capacity constraints, will produce equilibrium outcomes that ex-post can be decomposed into usual markup assumptions and a nonlinear cost residual reflecting the opportunity cost of selling rooms. Additionally, I model economies of scale via a measure of excess demand spillover that is recaptured within the firm, and show that increasing this internal spillover slackens the recovered soft capacity constraint.

From the Monte Carlo tests, I demonstrate two outcomes. First, I show that raising the probability of stockout via raising the variance of the demand shock results in price rationing at lower occupancy levels, but the effect is nonlinear. This explains why markets (or firms) with different demand volatility may exhibit dispersion in their capacity constraints. Second, I demonstrate that increasing the amount of recaptured excess demand among jointly-owned hotels results in less strict price rationing behavior, starting at the same threshold. The importance of this is in justifying the modeling assumption that a larger firm (that is, a firm controlling more properties in the same market segment) incurs nonlinear cost efficiencies related to its capacity constraint.

### A.1 Recovery of Convex Costs

Consider a monopolist hotel  $j$  who faces logit demand in period  $t$ :

$$u_{jt} = 0.5 - p_{jt} + \xi_t + \epsilon_{jt}, \tag{14}$$

where  $\xi_t$  is a random demand shock distributed  $N(\mu, v)$ , and  $\mu$  is observed by the hotel but the value of  $\xi$  is not. This random shock reflects that while market conditions may be known, hotels face an uncertain flow of demand. The hotel has a capacity constraint  $\kappa = 0.4$ . The hotel sets a single price that maximizes expected profits in period  $t$ . Marginal costs are a constant 0:

$$\begin{aligned}
\Pi_{jt}(p_{jt}; \xi_t) &= \max_{p_{jt}} p_{jt} E(\min(s_{jt}(p_{jt}; \xi_t), \kappa)) \\
&= \max_{p_{jt}} p_{jt} \int \min(s_{jt}(p_{jt}), \kappa) d\xi
\end{aligned} \tag{15}$$

All demand  $s_{jt} > \kappa$  is forfeited, and hence the hotel will skew prices higher than the unconstrained optimum to avoid the foregone revenue in stockout. The degree which the hotel raises these prices is based on the risk of stockout, the uncertainty of which is produced by the variance of  $\xi$ . By varying the average of the shock, I adjust the probability of stockout ( $Pr(s_{jt}(p_{jt}, \xi_t) > \kappa)$ ). There is a single unique optimal price  $p_{jt}(\mu_t)$  at each value of  $\mu$ .

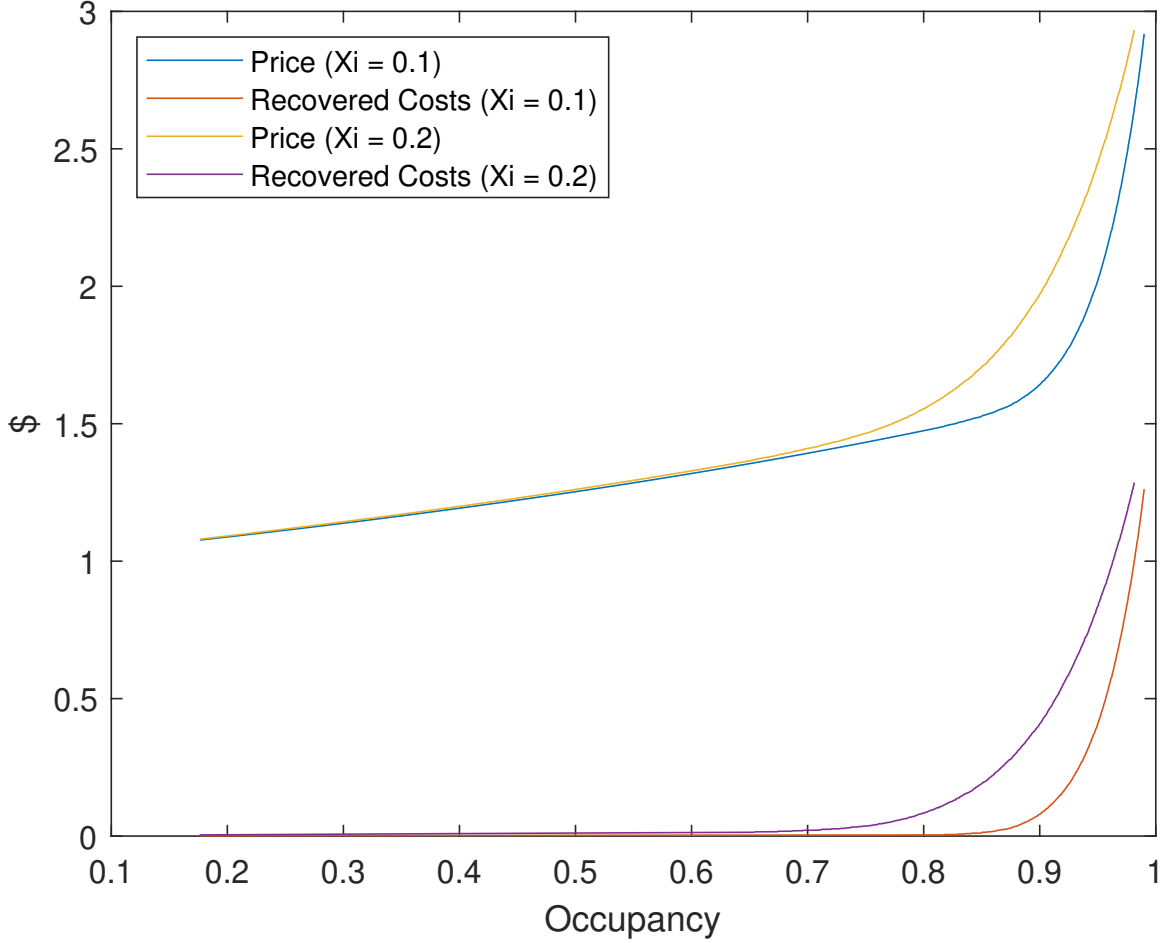
I simulate the above as follows, using  $T = 1000$  and  $n = 1000$ :

1. Given a draw of  $\mu_t$ , simulate the integral of  $\xi$  via  $n$  Halton draws and recover the expected quantity and profit for a starting value of  $p_{jt}$ .
2. For a uniform distribution of values  $\mu_t = [-2, 2]$ , solve for the expected profit-maximizing prices  $p_{jt}(\mu_t)$ , then determine quantities  $s_{jt}(p_{jt})$  given  $\xi_t = \mu_t$ . As there is a unique  $p(\mu)$  for each value of  $\mu$ , this latter simplification ensures that there is a one-to-one mapping of occupancy to prices.
3. Using the known demand system and observed equilibrium quantities, calculate the ex-post markups  $\Omega = - \frac{\partial s_{jt}(p_{jt})}{\partial p_{jt}} s_{jt}(p_{jt})$  and recover "as if" marginal costs  $\hat{c} = p_{jt} - \Omega$ .
4. Compare the recovered  $\hat{c}$  to the true marginal cost of 0.

Figure 1 presents the outcome of the monopolist's simulation for  $v = \{0.1, 0.2\}$ . When the risk of stockout is effectively zero, expected quantities are a distribution of interior solutions, and so the profit-maximizing price is equivalent to the unconstrained problem's solution. In this case, the recovered marginal costs are accurate as we precisely know the demand system. However, as the risk of stockout increases, the hotel's expected quantities include cases where rationing quantity against high demand is optimal. The demand system is misspecified in these cases, and so the recovered marginal cost values are greater than the truth. The residual values  $\zeta = \hat{c} - c > 0$  are increasing in occupancy, as the hotel rations its capacity more strictly as it approaches full capacity. Furthermore, as the probability

of stockout at any given  $\mu$  increases in  $v$ , the rationing threshold—the level of occupancy where nonlinear pricing begins—is lower when  $v$  is higher.

Appendix Figure 1: Simulated Prices and Recovered Costs (1)



While hotel rationing is a black-box process in practice and extremely challenging to estimate via explicit models of capacity-constrained supply, the above suggests that for an estimated demand system  $D(p)$  and a capacity constraint  $\bar{s}$ :

$$p - \frac{\partial D(p)}{\partial p} s(p) = \hat{c} = \underbrace{c}_{\text{True Marginal Cost}} + \zeta \underbrace{\frac{s(p)}{\bar{s}}}_{\text{Residual Value}} \quad (16)$$

which allows for the standard IO toolkit of demand estimation and conduction assumptions to be employed. The following section looks at how scale affect the functional form of  $\zeta(\cdot)$ ,

particularly in how these outcomes can be interpreted as cost efficiencies.

## A.2 Demand Spillover and Constraints

When the firm operates multiple hotels, some excess demand at any given hotel can be recaptured by its other properties instead of discarded. Here, I demonstrate that the degree of demand spillover affects the shape of the nonlinear capacity constraint, while holding firm conduct constant. I update the previous example to now contain two hotels with zero marginal costs: Hotel 1 is constrained as in the prior section. Hotel 2 is unconstrained, representing the relatively large mass of remaining rooms operated by the hotel (this may also be read as by the rest of the firm's properties). This assumption will be later relaxed. Consumer utility for each hotel is:

$$\begin{aligned}
 u_{1t} &= 0.5 - p_{1t} + \xi_t + \epsilon_{1t} \\
 &= \delta_{1t} + \epsilon_{1t} \\
 u_{2t} &= 1 - p_{2t} + \epsilon_{2t} \\
 &= \delta_{2t} + \epsilon_{2t}
 \end{aligned} \tag{17}$$

given  $\xi_t \sim N(\mu_t, 0.15)$ . Profit for the monopolist is determined by setting joint profit-maximizing prices in expectation of  $\xi$ .

$$\begin{aligned}
 \Pi_t(p_{1t}, p_{2t}; \xi_t) &= \max_{p_{1t}, p_{2t}} p_{1t} E(\min(s_{1t}(p_{1t}, p_{2t}; \xi_t), \kappa)) + p_{2t} E(s_{2t}(p_{1t}, p_{2t}; \xi_t)) \\
 &= \max_{p_{1t}, p_{2t}} p_{1t} \min(s_{1t}(p_{1t}, p_{2t}), \kappa) + p_{2t} s_{2t}(p_{1t}, p_{2t}) d\xi
 \end{aligned} \tag{18}$$

Importantly, there is a spillover rule for excess demand for Hotel 1, where quantities demanded greater than  $\kappa$  are reallocated at logit probabilities to Hotel 2 and the outside option, scaled by a spillover parameter  $d$ :

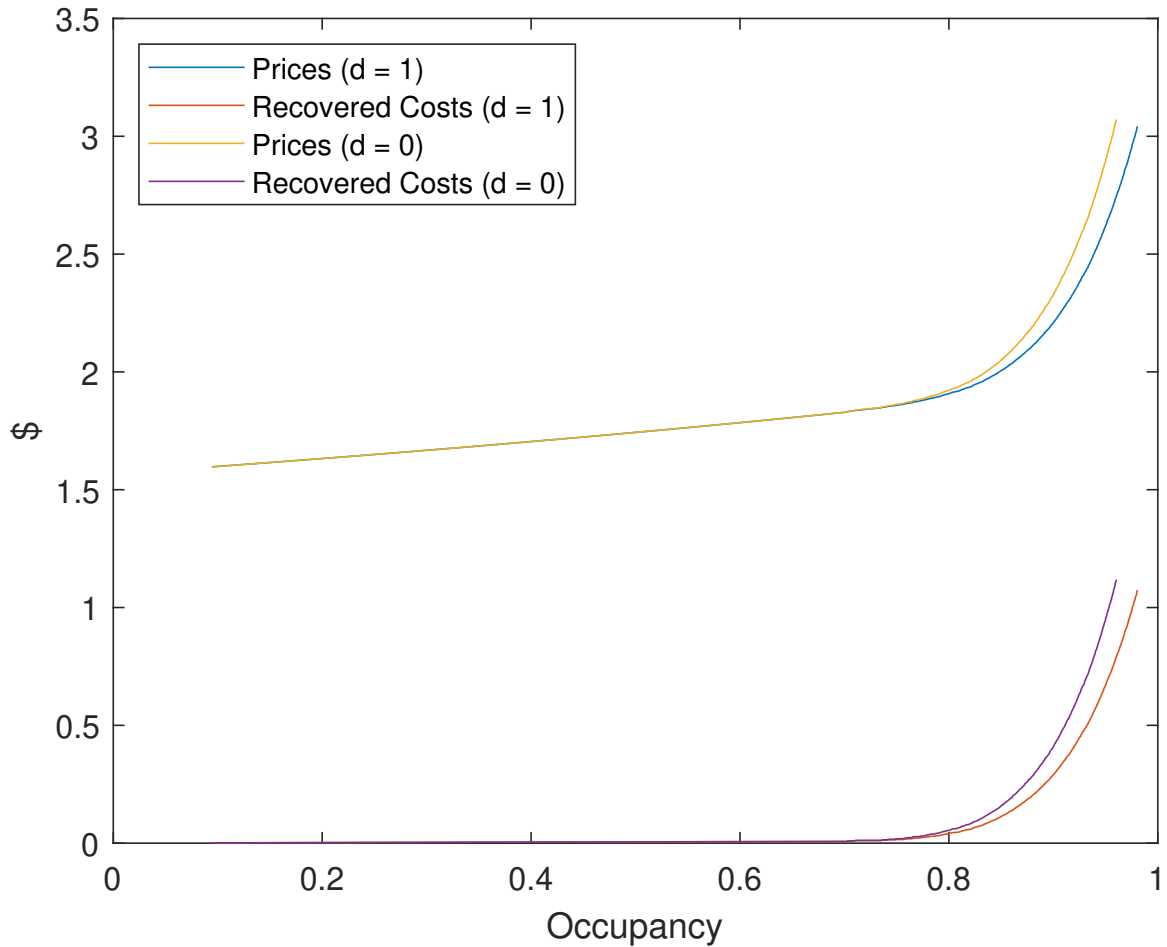
$$s_{2\uparrow, t} = d \mathbb{1}(s_{1t} > \kappa) (s_{1t} - \kappa) \frac{\exp(\delta_{2t})}{1 + \exp(\delta_{2t})}, \tag{19}$$

and hence:

$$s_{2t} = \frac{\mathbb{P}^{\exp(\delta_2)}}{1 + \sum_{j=1,2} \exp(\delta_j)} + s_{2j1;t} \quad (20)$$

Intuitively, as  $d : 0 \rightarrow 1$ , more revenue is recaptured in the case of stockout and the effects of rationing on Hotel 1's outcomes are diminished. The Monte Carlo simulation is solved as in the prior case, demonstrating this outcome for  $d \in \{0, 1\}$ . Figure 2 displays these results: at  $d = 1$ , the steepness of the price rationing is diminished versus  $d = 0$ , and so too is the recovered convex marginal cost curve. As the probability of facing stockout is the same in each case—the spillover rule does not affect the distribution of  $\xi$ —the starting point of the slope is unaffected.

Appendix Figure 2: Simulated Prices and Recovered Costs (Small Hotel)



In the above example, I assume that Hotel 1 is massless: Hotel 2 faces no capacity constraints

and can infinitely absorb excess demand. The effect of demand spillover in practice is theoretically ambiguous without this assumption, as hotels may also ration in excess to ensure they are able to absorb any expected excess demand from sister hotels. To test the strength of this assumption, I repeat the above scenario where both hotels are “large” in relation to each other, with reciprocal spillovers. Here,  $\xi_{jt}$  is multivariate normal and distributed iid  $N(\mu_t, 0.15)$ , and hotels 1 and 2 face constraints  $(\kappa_1, \kappa_2) = (0.25, 0.3)$ . Utilities are:

$$\begin{aligned}
u_{1t} &= 1 - p_{1t} + \xi_{1t} + \epsilon_{1t} \\
&= \delta_{1t} + \epsilon_{1t} \\
u_{2t} &= 2 - p_{2t} + \xi_{2t} + \epsilon_{2t} \\
&= \delta_{2t} + \epsilon_{2t}
\end{aligned} \tag{21}$$

and the firm’s profit-maximization problem is as before but with both firms facing their capacity constraints. The spillover rules are hence defined for each hotel:

$$s_{jj} = d1(s_{j;t} > \kappa_j)(s_{j;t} - \kappa_j) \frac{\exp(\delta_{jt})}{1 + \exp(\delta_{jt})}, \tag{22}$$

and shares for each hotel are (dropping the  $t$  subscript):

$$s_j(p_j, p_{-j}; \xi) = \frac{\exp(\delta_j)}{1 + \frac{\exp(\delta_k)}{\kappa_k}} + s_{jj} \tag{23}$$

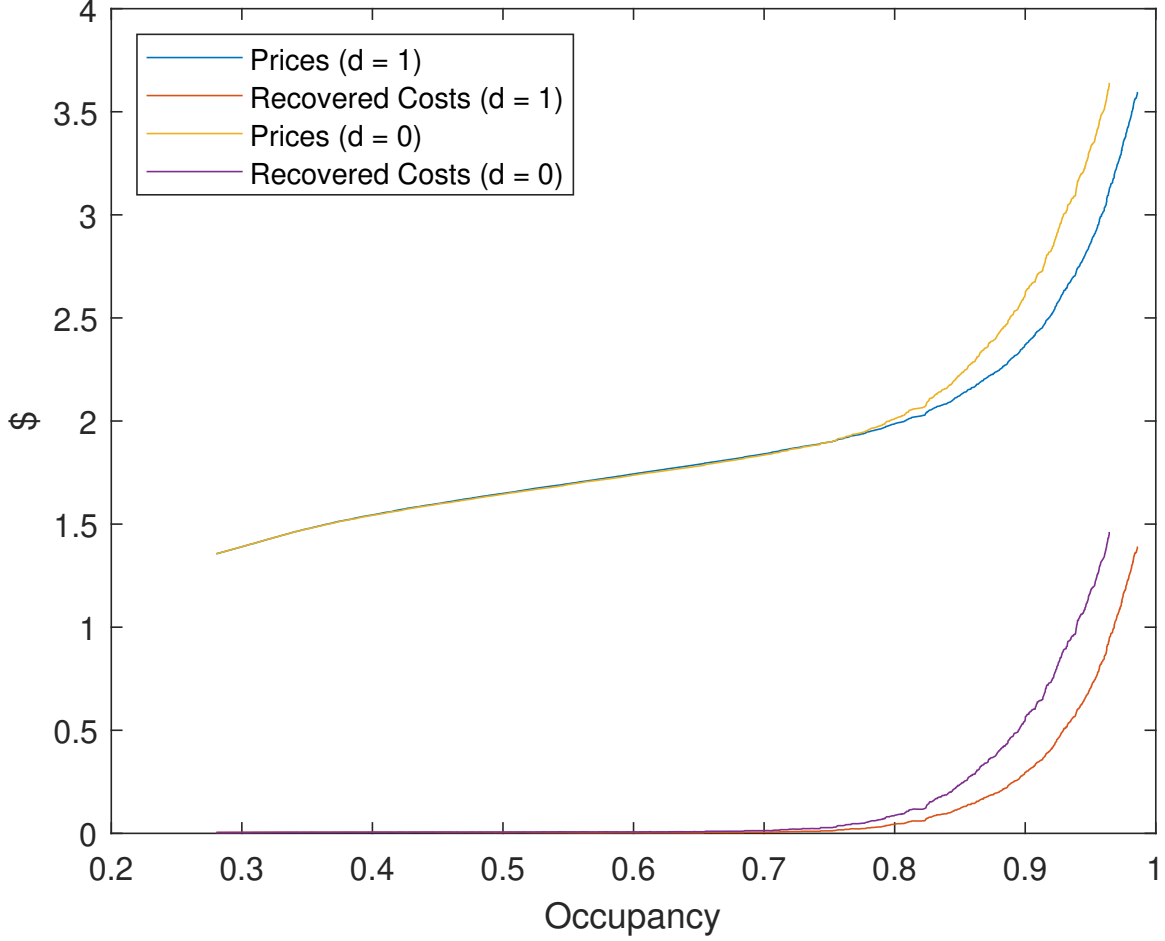
Figure 3 shows that the same pattern is observed: moving from zero spillover to logit spillover results in a slackening of the soft capacity constraint.

## Appendix B Elasticities and Markups

In this section I use terminology more specific to logit demand. Demand elasticities  $\mathcal{E}_{hk} = \frac{\partial s_h / \partial p_k}{s_h}$  in the nested logit case are a  $H \times H$  matrix, given segments  $h \in H$  with respective nests  $\ell(h)$ . For segments  $h$  and  $k$ , the  $(h, k)$  element of the elasticity matrix is:



Appendix Figure 3: Simulated Prices and Recovered Costs (Large Hotel)



$$\mathcal{E}_{hk} = \frac{\partial s_h p_k}{\partial p_k s_h} = \begin{cases} \sum_{j \neq h} \frac{\alpha s_j p_j}{1 - p_h(1 - \rho s_{hj} - (1 - \rho)s_h)} & \text{if } h = k \\ -\alpha s_k p_k \left( 1 + \frac{1}{s \cdot (h)} \right) & \text{if } h \neq k \text{ and } \ell(h) = \ell(k) \\ -\alpha s_k p_k & \text{if } h \neq k \text{ and } \ell(h) \neq \ell(k) \end{cases} \quad (24)$$

where  $s_h$  denotes the market share of segment  $h$ .

Cournot-Nash markups are  $\Omega = - \Omega \cdot (S_p^{-1})^0 s$ . The ownership matrix  $\Omega$  is a block diagonal matrix determining whether firm-segments  $h_f$  and  $k_f$  are in the same parent company's set of operated segments  $\mathcal{H}_f$ . The dimensions of this matrix are hence  $\mathcal{H} \times \mathcal{H}$ , where each "product" is a firm-segment observation.

$$\Omega = \begin{cases} 8 & \\ < 1 & \text{if } h_f, k_f \in \mathcal{H}_f \\ \vdots & \\ 0 & \text{otherwise} \end{cases} \quad (25)$$

Taking the linear nested logit demand equation  $\log(s_h/s_0) = x_h\beta + \alpha p_h + \rho \log(s_h/s_{\cdot(h)})$ , the matrix of derivatives  $\frac{\partial p_j}{\partial s_k}$  is as follows for the  $(h_f, k_f)$  element. The  $f$  subscripts are dropped below as the demand system does not differentiate between firms within a segment, and so the derivatives for two firm-segments in the same segment are equal.

$$S_p^{-1} = \frac{\partial p_h}{\partial s_k} = \begin{cases} 8 & \\ \frac{1}{s_h} + \frac{1}{s_{\cdot(h)}} + \frac{1}{s_0} & \text{if } h = k \\ \frac{1}{s_{\cdot(k)}} + \frac{1}{s_0} & \text{if } h \neq k \text{ and } k \in \ell(j) \\ \vdots & \\ \frac{1}{s_0} & \text{if } h \neq k \text{ and } k \notin \ell(h) \end{cases} \quad (26)$$

## Appendix C Instrument Robustness

The literature on testing of weak instruments provides for a range of simple approaches for the linear 2SLS specification. For the price instrument  $z_{hn}$ , I find a Montiel-Pleuger Effective F statistic of 153.0 versus a 5% critical value of 37.4. The Anderson-Rubin—with a Chi-sq of 85.07—estimated 95% confidence set of  $[-0.047, -0.028]$  heavily overlaps the estimated confidence set  $[-0.046, -0.027]$ .

No equivalent to the Effective F statistic exists in the  $k = 2$  nested logit case with multiple endogenous regressors. To assess the nest instrument  $z_{hn}$ , I report the Kleibergen-Paap robust F statistic of 36.9. Additionally, the nested logit specification shows Sanderson-Windmeijer F statistics for individual regressors at 75.9 (prices) and 138.0 (log inside-nest share). An Anderson-Rubin test reports a Chi-sq of 105.46.

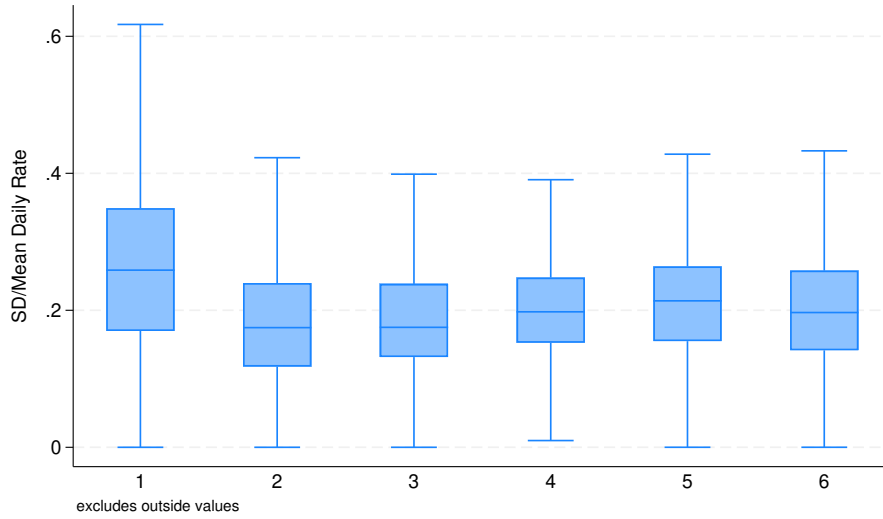
## Appendix D Additional Tables and Figures

Appendix Table 1: Elasticities by Segment

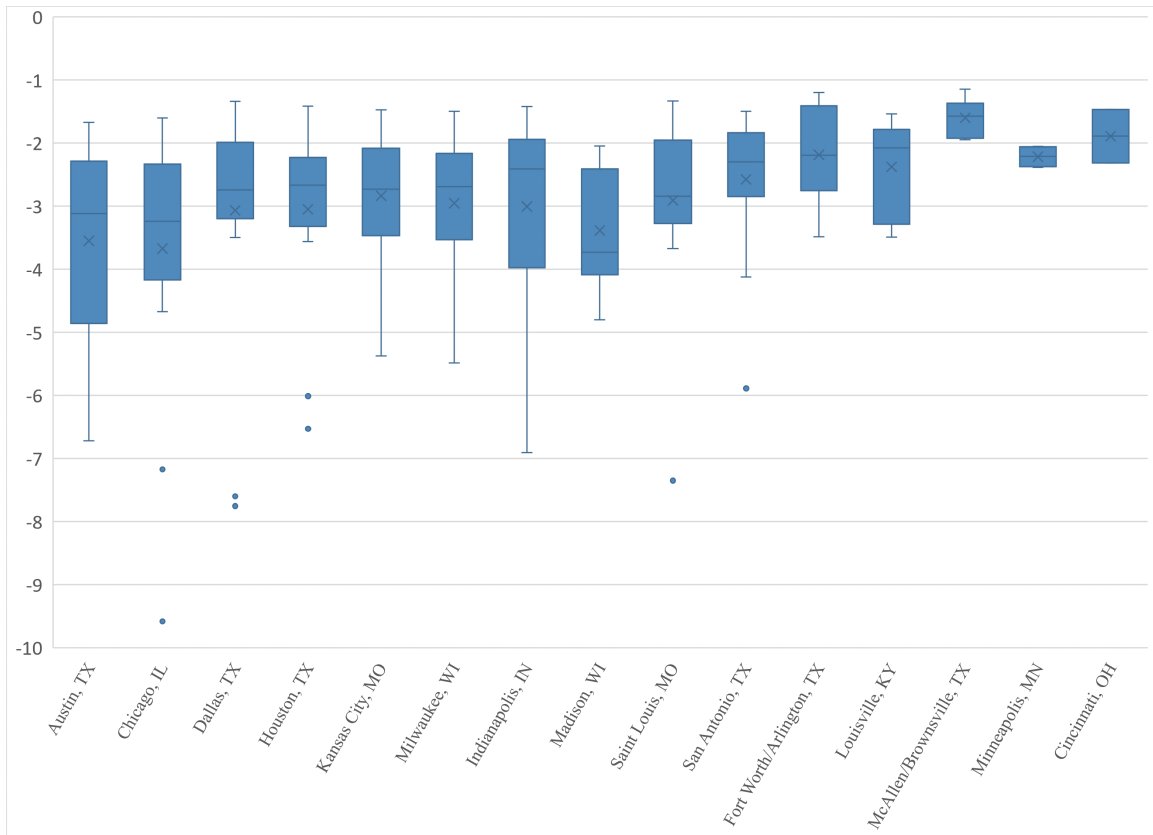
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	
Luxury	1	-5.880	1.623	0.663	0.107	0.018	0.095	0.032	0.004	0.003	0.022	0.075	0.089	0.124	0.098			0.018	
Upper Upscale	2	0.079	-2.883	0.463	0.237	0.084	0.083	0.077	0.046	0.042	0.015	0.024	0.070	0.168	0.053	0.034	0.005	0.007	
Upscale	3	0.996	-2.726	0.285	0.126	0.087	0.018	0.058	0.049	0.061	0.022	0.021	0.053	0.165	0.043	0.030	0.004	0.008	
Upper Midscale	4	0.080	1.050	0.569	-2.516	0.128	0.086	0.019	0.058	0.062	0.021	0.021	0.060	0.133	0.057	0.035	0.003	0.008	
Midscale	5	0.984	0.567	0.343	-1.937	0.082	0.020	0.053	0.053	0.065	0.023	0.021	0.053	0.133	0.048	0.033	0.003	0.007	
Economy	6	0.080	1.033	0.514	0.277	0.109	-1.486	0.019	0.060	0.043	0.051	0.018	0.047	0.145	0.049	0.036	0.003	0.009	
Luxury	7	0.005	0.067	0.022	0.018	0.006	0.004	-5.901	0.747	0.375	0.311	0.101	0.218	0.081	0.147	0.059	0.027	0.004	0.007
Upper Upscale	8	0.005	0.062	0.024	0.012	0.004	0.004	0.201	-3.363	0.421	0.381	0.145	0.200	0.069	0.174	0.053	0.032	0.006	0.007
Upscale	9	0.005	0.054	0.024	0.014	0.005	0.004	0.152	0.519	-2.964	0.510	0.185	0.183	0.061	0.151	0.051	0.032	0.006	0.006
Upper Midscale	10	0.005	0.046	0.026	0.014	0.005	0.004	0.130	0.419	0.452	-2.341	0.217	0.183	0.052	0.142	0.046	0.031	0.005	0.006
Midscale	11	0.005	0.045	0.026	0.013	0.005	0.004	0.123	0.425	0.446	0.588	-1.996	0.187	0.052	0.145	0.046	0.032	0.005	0.006
Economy	12	0.005	0.055	0.024	0.013	0.004	0.004	0.203	0.557	0.406	0.461	0.176	-1.519	0.055	0.149	0.048	0.031	0.005	0.007
Luxury	13	0.005	0.061	0.023	0.014	0.005	0.004	0.018	0.075	0.056	0.054	0.020	0.021	-6.571	1.491	0.553	0.315	0.056	0.052
Upper Upscale	14	0.005	0.054	0.026	0.011	0.004	0.004	0.020	0.070	0.050	0.056	0.021	0.023	0.577	-3.431	0.455	0.282	0.050	0.061
Upscale	15	0.005	0.061	0.024	0.016	0.005	0.004	0.021	0.070	0.053	0.058	0.021	0.023	0.612	1.410	-3.719	0.344	0.044	0.066
Upper Midscale	16	0.005	0.059	0.029	0.017	0.006	0.005	0.019	0.066	0.051	0.057	0.021	0.023	0.538	1.340	0.555	-3.367	0.037	0.089
Midscale	17	0.005	0.056	0.022	0.010	0.004	0.003	0.018	0.080	0.053	0.048	0.018	0.024	0.696	1.808	0.451	0.249	-3.165	0.048
Economy	18	0.005	0.058	0.034	0.015	0.006	0.007	0.020	0.072	0.038	0.037	0.015	0.024	0.497	1.472	0.476	0.410	0.037	-2.260

Segments within the same nest are highlighted.

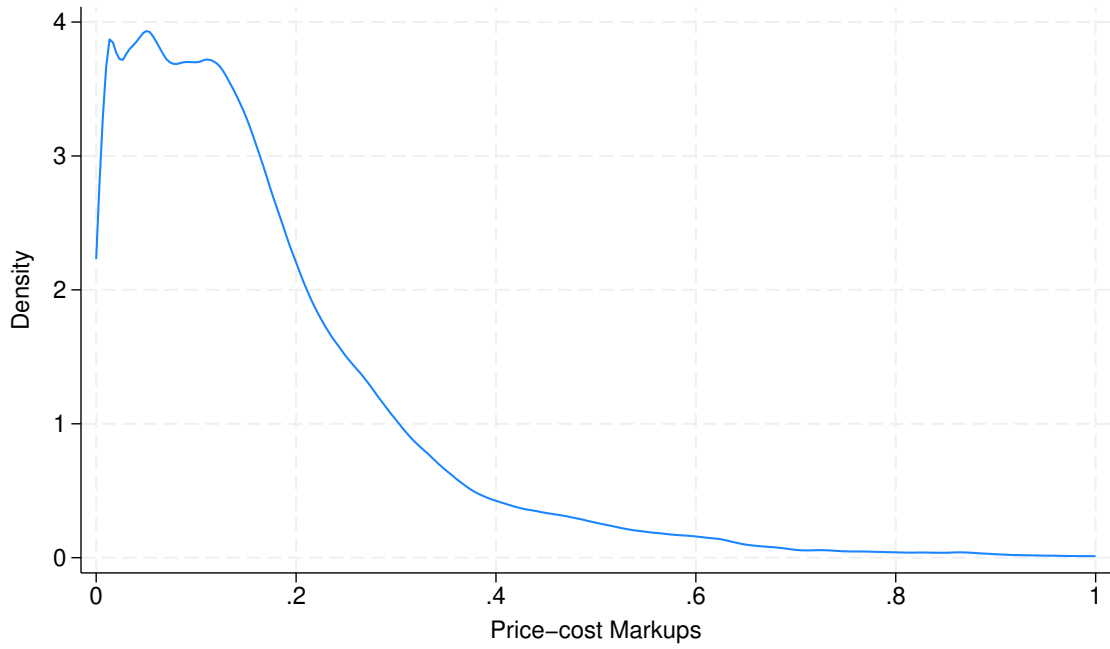
Appendix Figure 4: Ratio of Within-segment SD to Mean Prices



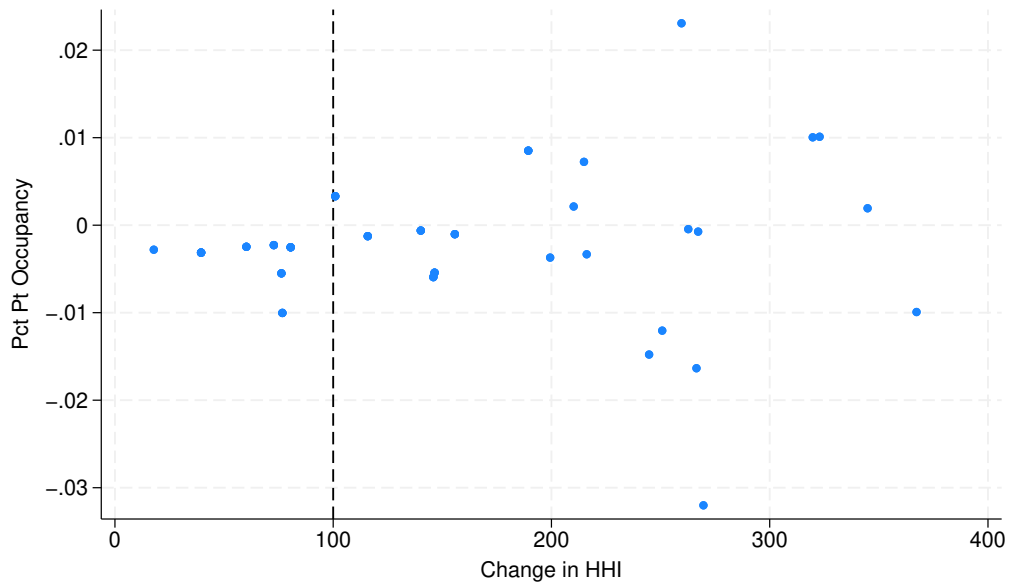
Appendix Figure 5: Own-Price Elasticities by City



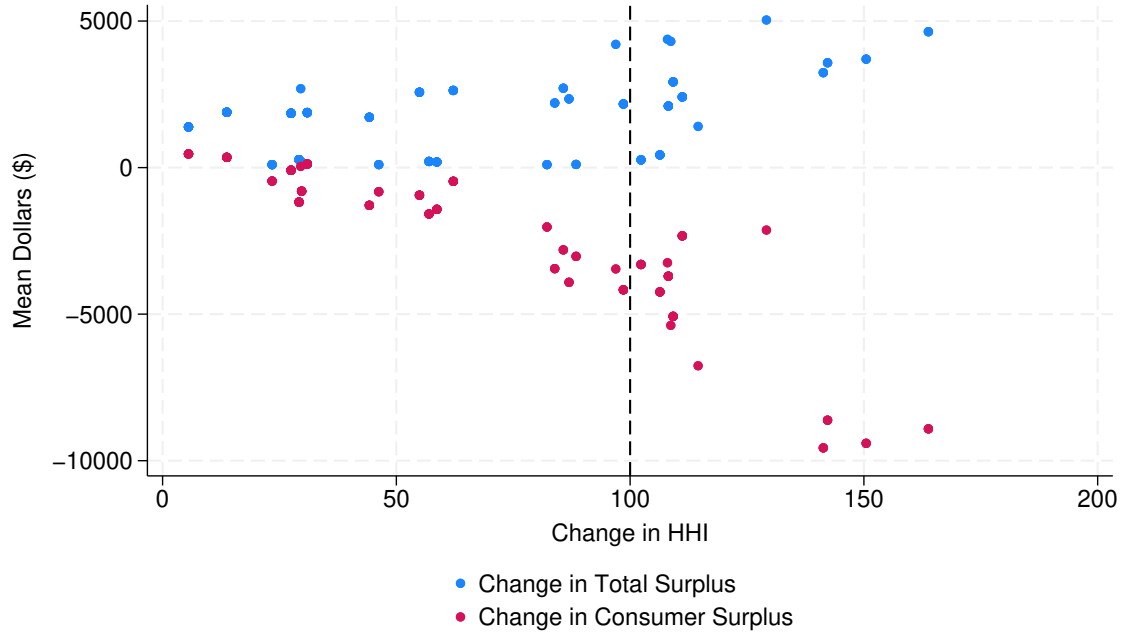
Appendix Figure 6: Distribution of Estimated Markups



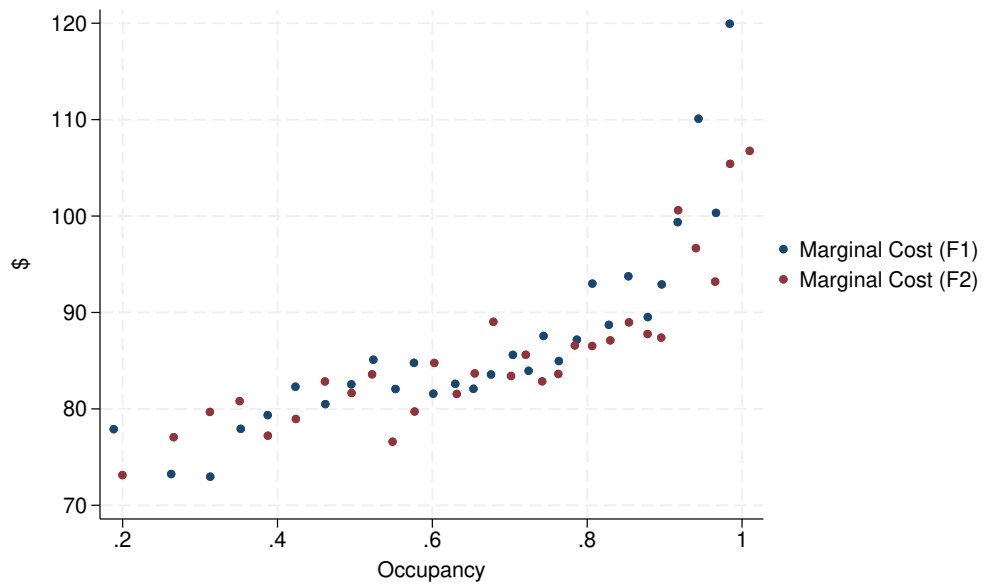
Appendix Figure 7: Policy Experiment Results (Occupancy)



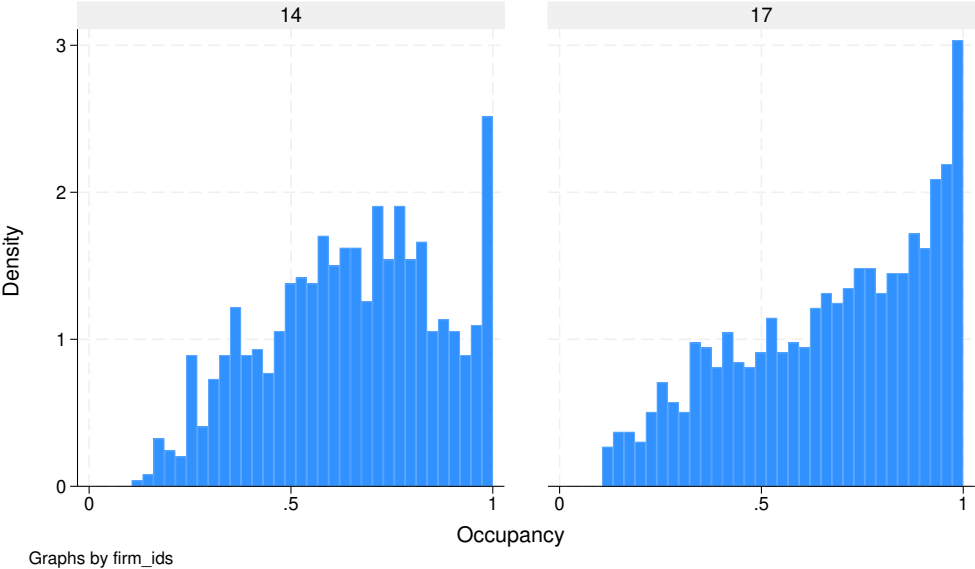
Appendix Figure 8: Policy Experiment Results (Welfare, Less Concentrated Market)



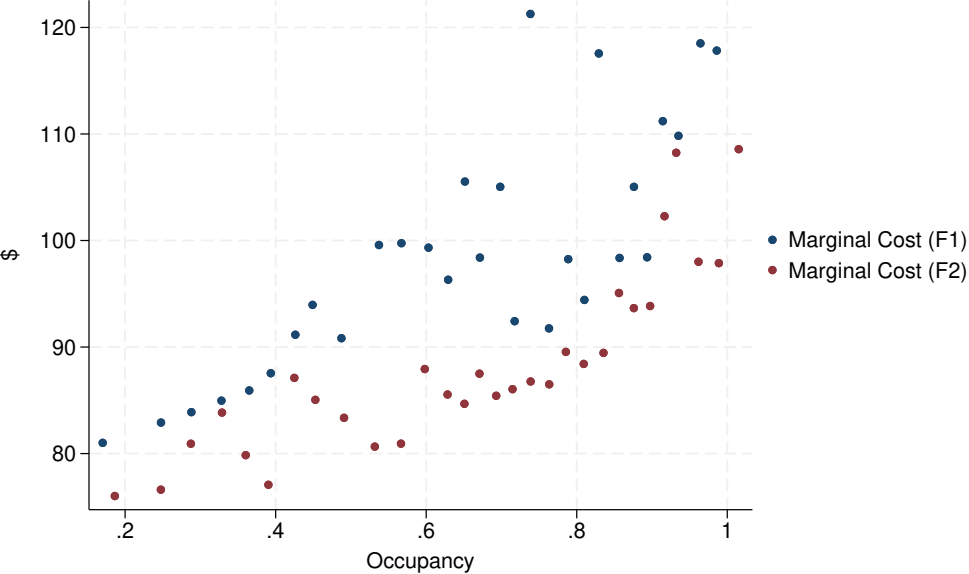
Appendix Figure 9: Merging Firms' Costs (Merger 1)



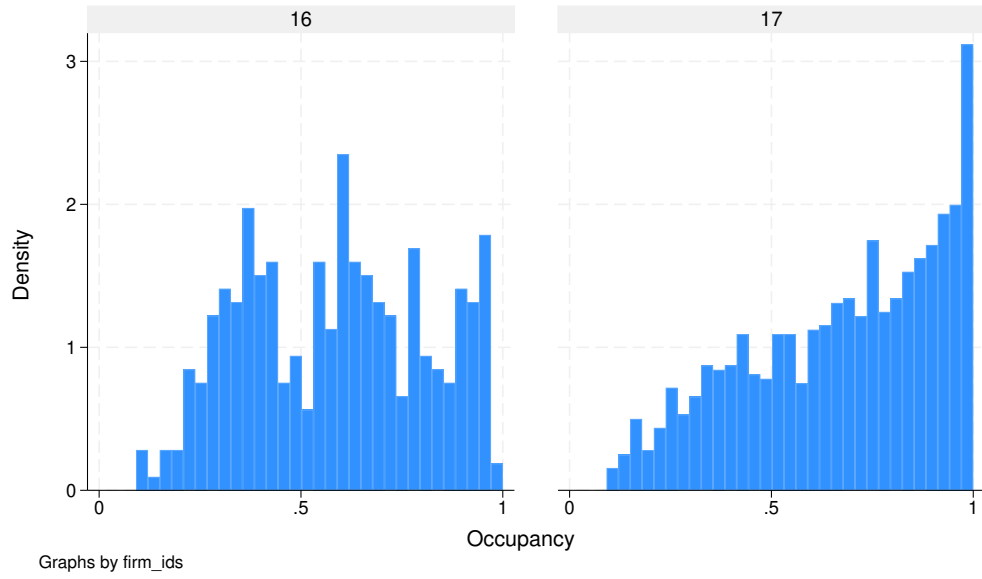
Appendix Figure 10: Merging Firms' Occupancy (Merger 1)



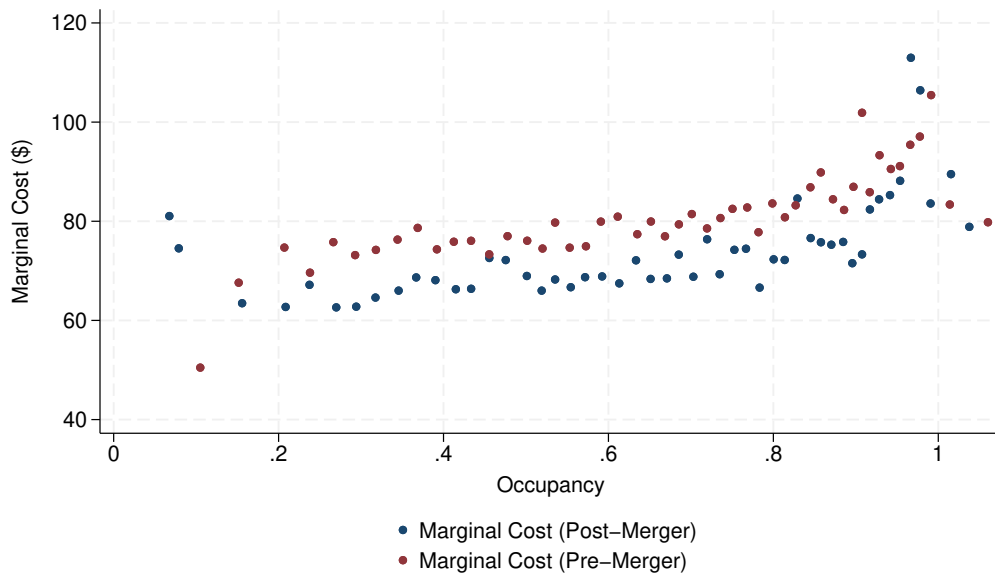
Appendix Figure 11: Merging Firms' Costs (Merger 2)



Appendix Figure 12: Merging Firms' Occupancy (Merger 2)



Appendix Figure 13: Changes in Merging Firms' Costs (Merger 1)





Appendix Figure 14: Changes in Merging Firms' Costs (Merger 2)

