Multimarket Contact, Pricing and Franchising: A Study of the Hotel Industry in Texas

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Abstract

We investigate the effect of multimarket contact (MMC) on collusive pricing in the hotel industry, a setting where most firms often face the same competitors in different markets. The paper makes two contributions. First, we allow for (partial) vertical control, a feature that is central in this industry given the widespread use of franchising and vertical restraints. Specifically, we use a structural model that estimates the degree of vertical control while, at the same time, allowing for joint profit-maximizing behavior that depends on the degree of MMC between hotels. Second, as opposed to prior literature, we do not use ad-hoc geographic market definitions; instead, we rely on data-driven approaches to delineate markets. Counterfactual results show that hotels with higher levels of multimarket contact charge higher prices and that the degree of vertical control is important in the estimation of this relationship.

1 Introduction

Multimarket contact (MMC) is frequently observed in retail and service industries: competitors face the same rivals in different geographic markets. The concurrent nature of competition that emerges in these cases can create incentives that are conducive to supra-competitive prices. Bernheim and Whinston (1990) show that competition of firms with multiple contacts in a repeated game setting can give rise to collusive equilibria. Since Bernheim and Whinston (1990), several empirical studies have confirmed this theoretical prediction in various industries: airlines (e.g., Evans and Kessides, 1994; Gimeno and Jeong, 2001; Ciliberto and Williams, 2014), cement (Jans and Rosenbaum, 1996), movie (e.g., Feinberg, 2014), lumber (Khwaja and Shim, 2017) and hotel (e.g., Fernandez and Marin, 1998; Silva, 2015).

This paper contributes to the empirical literature on the effects of MMC in two dimensions. First, we take into account the extent of vertical control that is often

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observed in these retail industries. While the hotel industry is often characterized by a vertical separated structure, an important degree of vertical control is exercised by the upstream firms via franchising contracts with the downstream units. Importantly, some degree of vertical control is necessary for the MMC collusive equilibria to emerge: if the downstream firm is fully independent from the upstream unit, then there is little reason for the downstream to internalize or consider the pricing behavior of hotels outside its market. On the other hand, if the upstream firm has partial control of downstream operations across multiple franchisors, in particular as it pertains to pricing, then theoretical incentives for collusion become relevant. Intuitively, a firm may start a price war in one market in retaliation to a rival firm's reluctance to adhere to a collusive price in another market.

Even though franchisors exert control over franchisees in various aspects of managerial decisions, it is still unclear whether franchisors have some level of influence on pricing decisions since direct price control by franchisors, known as retail price maintenance, is not permitted in many countries, including the United States. Despite this prohibition, franchisors include various stipulations in franchising contracts, either mandatory or voluntary, to influence franchisees. Examples of these stipulations include central reservation systems, regional marketing, and group selling with other franchisees. Thus, the degree to which upstream firms control downstream units' pricing is an empirical question. In this paper, we aim to measure the effect of MMC on pricing while, at the same time, also estimating the the degree of vertical control in the hotel industry.

The second contribution of this paper is to implement data-driven approaches for delineating markets. Market definition is a key industrial organization concept and is at the core of antitrust debates. Yet, much debate surrounds the proper methodology for defining the sets of products or geographic areas across which competition is nonexistent (or minimal). In our application, geographic market definition is essential for determining when (or if) multi-market contact exists and how intense it is (i.e. in how many other markets does such contact occur).

A commonly used and uncontroversial approach is to study geographically isolated markets: distantly located clusters of cement producers, city-route pairs served by airlines, and third-party defined tourism areas for hotels. While these approaches are valid and sound, they cannot be applied for many retail or service industries where competition across geographic areas is intertwined and no obvious boundaries exist. Although firms in these industries are spread widely over regional areas, it is often the case that their operations show important agglomeration patterns. This suggests that competition is likely more localized than what a broad geographic market definition approach (e.g. a nationwide or statewide market) would suggest. We rely on this insight to delineate geographic markets using a data-driven approach.

Specifically, we use a density-based spatial clustering application with noise (DBSCAN) to identify groups of hotels that are located in a common cluster (or geographic market).[1] This clustering approach is amenable to structural estimation and counterfactual analysis, which require markets to contain mutually exclusive sets of firms.[2]

Due to data availability, our analyses focus on the hotel market in the Houston metropolitan statistical area (MSA). However, we note that the methods could be applied to other hotel markets or industries. We carry out two types of empirical analyses. First, we report reduced form evidence on the relationship between the degree of MMC and price levels. Second, we test the effect of MMC on pricing in a structural model of the hotel market where partial vertical control is allowed (and estimated).

The reduced form results show that hotels with higher levels of multimarket contact charge higher prices. These results are consistent with prior studies in other industries, such as airline and cement (Evans and Kessides, 1994; Gimeno and Jeong, 2001), as well as in the hotel industry (Fernandez and Marin, 1998; Silva, 2015). The structural model of demand and supply produces a similar result: a greater degree of MMC results in a greater deviation from the Bertrand-Nash competitive equilibrium. Counterfactual analyses reveal that, all else equal, the removal of MMC would decrease equlibrium prices by 1.5%. While the inclusion of partial vertical control in the model still confirms that MMC produces higher equilibrium prices, its inclusion is important as the magnitude of the effect is significantly different than that observed in a (less flexible) model that assumes full vertical control. (Molnar et al., 2013; Ciliberto and Williams, 2014; Khwaja and Shim, 2017).

The paper is organized as follows. Section 2 reviews related work. The data are described in Section 3. Reduced form and structural models are presented in Section 4. Section 5 presents the results. Section 6 concludes and discusses possible extensions for future research.

2 Literature Review

Bernheim and Whinston (1990, hereafter BM) are among the first researchers to propose a theoretical model in which multimarket contact can make collusion a feasible equilibrium in a repeated game setting. In this setting, there are N^m firms (firm $j = 1, \cdots, N^m$) in market $m = 1, \cdots, M$. The profit function of firm j is $\pi_j^m = \pi_j^m(p_j^m, p_k^m)$. If there is only one market ($M = 1$), firm j faces the following incentive compatibility constraint when deciding whether to cooperate:

$$\pi_j^m(R_j(p_k^m), p_k^m) + \frac{\delta}{1-\delta} v_j^m \leq \frac{1}{1-\delta} \pi_j^m(p_j^m, p_k^m), \forall j \neq k \tag{1}$$

[1]We also probe the robustness of our results to another data-driven method. Specifically, we measure the price reaction slope of rival hotels and determine the distance after which such slope ceases to exist. Details of this distance metric approach are contained in Appendix B.

[2]Since the distance metric approach does not produce mutually exclusive geographic markets, it can only be applied to our reduced form analysis. More details are provided later in Appendix B.

where $R_j()$ is the best response of firm j given p_k^m, v_j^m is the payoff under optimal punishment, and δ is the discount factor. The left hand side in Equation 1 represents the payoff from deviation, while the right hand side is the payoff from cooperation.

With multiple markets ($M > 1$), BM show that pooling the incentive compatibility constraints across different markets creates inter-dependency among firms across markets. This means that when a firm chooses the price in a market, it takes into consideration the responses of rivals' in the market as well as the response of rivals in other markets. The pooling incentive compatibility constraint is as follows:

$$\sum_m \pi_j^m(R_j(p_k^m), p_k^m) + \frac{\delta}{1-\delta} v_j^m \leq \sum_m (\frac{1}{1-\delta} \pi_j^m(p_j^m, p_k^m)) \tag{2}$$

BM show that the above pooling incentive compatibility constraint does not guarantee cooperation among firms since the pooling constraint can be equivalent to the simple sum of the constraints in all markets if competition among all the markets is homogeneous. However, if markets are heterogeneous, or if firms provide differentiated products across markets, the pooling constraint is satisfied, implying that MMC can create incentives for firms not to deviate from the cooperation equilibrium.

Since BM's theoretical framework, a number of empirical studies in several industries have examined the effect of MMC on collusive behavior, especially focusing on the relation between MMC and prices. Even though results vary across studies, most empirical evidence has found support for BM's prediction: higher levels of MMC result in higher prices.

These prior empirical studies can be categorized into two groups: 1) reduced form models (Evans and Kessides, 1994; Gimeno and Woo, 1996; Fernandez and Marin, 1998; Waldfogel and Wulf, 2006; Silva, 2015; Bilotkach, 2011), and 2) structural models (Ciliberto and Williams, 2014; Khwaja and Shim, 2017; Molnar et al., 2013).

Most early studies in the literature fall in the first category. Evans and Kessides (1994), examine the effect of MMC in the airline industry. To deal with the possible endogeneity of MMC, the authors use fixed-effects and instrument variable models and find that carriers with high levels of MMC charge higher prices. Later studies evaluate how the interaction between other factors and MMC affect prices. For example, Fernandez and Marin (1998) test the interaction between market share and MMC, Gimeno and Woo (1996) analyze the interaction between strategic similarity and MMC, and Silva (2015) examines the role of vertical product differentiation on MMC. Unlike studies that test the effect of MMC on prices, Bilotkach (2011) analyzes the effect of MMC on non-price product characteristics (frequency of services), in the airline industry. Using the merger between US Airways and American West Airlines as an idiosyncratic shock that significantly changed levels of MMC, Bilotkach finds that the frequency of services is lowered in markets with higher levels of MMC after the merger.

These studies use reduced form models to examine the relationship between a firm's price (or another product characteristic) and the firm's exposure to MMC .

This approach requires a one-to-one correspondence between the dependent variable (price) and a firm's multimarket contacts (of which there can be many).To address this issue, these studies employ a measure of MMC that aggregates across all multimarket contacts that a firm faces in a given period (an MMC index such as the total number of MMC a firm faces). While a practical and needed simplification, the index treats all contacts equally thereby sweeping away any heterogeneity that may exist across all possible contacts that a firm may face in a market. Structural approaches, reviewed next, do not suffer from this limitation.

Structural studies rely on the approach introduced by Berry (1994) and Berry et al. (1995).These studies model all individual pairwise multimarket contacts that a firm faces. Specifically, conduct parameters are defined as a function of whether two rival firms in a market also face each other in other markets. An additional advantage of these studies is that counterfactual or welfare analyses can be carried out.For example, Ciliberto and Williams (2014) estimate conduct parameters capturing the effect of MMC in the airline industry, and find that airlines with high levels of MMC charge higher prices. In a similar vein, Molnar et al. (2013) examine the effect of MMC on deposit interest rates in the Italian retail banking industry. The authors find that banks with high levels of MMC set lower deposit interest rates thereby reducing consumer welfare.

All approaches (reduced form or structural) aimed at quantifying the effect of MMC on prices rely on a valid geographic market definition. Improperly defined or unjustified market delineations could result in biased estimates. When defining geographic markets, prior work has largely relied on ad-hoc procedures that are (often) well-justified by the institutional details of the industry being studied. For example, each city-pair route is treated as a distinct geographic market in the airline industry (Evans and Kessides, 1994; Gimeno and Woo, 1996; Ciliberto and Williams, 2014). [3]

In other cases, however, it is less clear whether an ad-hoc geographic market definition is reasonable. For instance, Jans and Rosenbaum (1996) use metropolitan cities with a 200 mile-limit as a market definition for the cement industry. Feinberg (2014) adapt similar strategies to define markets for movie theaters (mid-size metropolitan cities). Fernandez and Marin (1998) and Silva (2015) use government defined tourism or business districts to delineate geographic markets. In these cases, the resulting geographic markets are large; a consequent drawback of such market definitions is that the degree of MMC would be significantly underestimated. For example, it is reasonable to assume that a hotel on the outskirts of a large city (e.g. near the airport) does not compete head to head with a hotel located in the business downtown area; however, a broad market definition that includes all hotels in the city could consider these two hotels as being in the same geographic market.[4]

[3]This geographic market definition has also been used, and has been largely uncontested, in antitrust cases dealing with the airline industry.

[4]For instance, Fernandez and Marin (1998) identify entire large metropolitan areas such as Madrid and Barcelona as separate geographic markets.

One contribution of this paper is to incorporate and estimate the degree of vertical control in the modeling of MMC and its price effects. Franchising, one of the most widely used vertical contracts, is prevalent in the retail and service industries. Since resale price maintenance can be frowned upon by antitrust authorities, one might argue that franchisees are free to choose their pricing strategies and therefore vertical control is not important in the modeling of MMC. However, franchisors implement a variety of stipulations in their franchising contracts that may serve as a substitute for direct price control. These stipulations include nationwide advertising (Ater and Rigbi, 2015) and advanced pricing techniques (HNN, 2012).

Further, Kosová et al. (2013) empirically show that there is no difference in prices between corporate-owned and franchised hotels after controlling for the endogeneity of the choices of the organizational forms (corporate owning vs. franchising). This empirical evidence indirectly supports the notion that franchisors exert some level of control over the pricing policies of their franchisees.

Further support is provided by the language used in franchising contracts. We carried out a review of franchise disclosure documents (FDDs) in the hotel industry [5] and identified three mechanisms by which franchisors may directly (or indirectly) attain certain vertical control: a) revenue management systems and consulting services, b) national/regional marketing by franchisors, and c) regional/local marketing cooperatives by franchisees.

Taken together, the reviewed literature and the institutional details suggest that some degree of vertical control in franchising is likely. We treat this possibility as an empirical question that we address in our modeling.

3 Data

3.1 Data Source

The study focuses on hotels in Houston, Texas from the first quarter up to the fourth quarter in 2014. One reason to choose this location is that data availability is limited to Texas. Second, we intentionally choose a large city that is spread out over a large geographic area: it is not clear whether there is a single market or if this metropolitan area is composed of distinct clusters of competition. This approach contrasts with the usual strategy of circumventing the issue by, for example, restricting the analysis to small and isolated rural towns (which are then treated as separate geographic markets; e.g.Mazzeo (2002)).

Prices, quantities, capacity (No. of rooms), and brand affiliation are retrieved from *Source Strategies INC*. Hotel characteristics, such as facilities, amenities, and services, are collected from *TripAdvisor*.

[5] See Appendix A for details of this review

3.2 Market Definition: Clustering Approach[6]

Clustering algorithms, a non-parametric tool, groups observations into mutually exclusive sets such that observations in a cluster are more closely related to each other than they are to observations in other clusters. Although various clustering algorithms are available, we use a density-based spatial cluster algorithm with noise (DBSCAN) (Ester et al., 1996). We use this algorithm since DBSCAN is more data-driven approach without prior assumptions on data. DBSCAN does not require a pre-determined number of clusters. Unlike other clustering algorithms, such as the K-mean clustering and hierarchical clustering, DBSCAN can form clusters with little knowledge of markets. Further, the algorithm does not rely on other ex-ante (arbitrary) assumptions such as the number of clusters.

In clustering through DBSCAN, only two pre-determined parameters are required: the distance limit (among observations in a cluster) and the minimum number of nearby observations (points) in a cluster. Given these parameters, DBSCAN identifies core points, points that are surrounded by the minimum number of nearby points within the distance limit. Then, through an iterative process, clusters are determined by including all nearby observations (non-core points) within the distance limit. Observations that are neither core points nor a part of any cluster are considered as noise points. If, in a given iteration, a core point is located sufficiently close to other core points, the corresponding clusters are combined.

The two parameters (the minimum number of nearby points and the distance limit) need to be set by the researcher prior to applying the algorithm's iterative clustering procedure.

We rely on institutional knowledge from the industry and set the minimum number of points to four. A common practice among hotel managers is to base pricing decisions based on a benchmark of pricing decisions by nearby hotels (the so-called "competitive set"). It has been documented that this set usually contains the four nearest hotels in the same class (Kalnins, 2006; Rezvani and Rojas, 2020).[7]

To set a reasonable distance limit, one can use information on the distribution of pair-wise distances between hotels. For instance, a distance limit can be set to a level where a reasonable fraction of pair-wise distances are captured. To do this, we focus on the pairwise (Euclidean) distances between each hotel and its four nearest competitors [8]. Using this set of distances, we select each hotel's distance to the fourth most distant competitor and visualize its cumulative distribution (Figure 1).

As the distance increases, more hotels have their 4th nearest competitor within such distance. Based on Figure 1), we use 0.04 as the distance limit (approximately 1.5 miles), as this value captures the large majority of pair-wise distances (94.05%).

[6]An alternative method for defining markets and its use as a robustness check is detailed in Appendix B.

[7]Results with different numbers of minimum nearby points (3 and 5 nearby points) are qualitatively similar.

[8]We select the four nearest competitors based on the institutional aspect just described

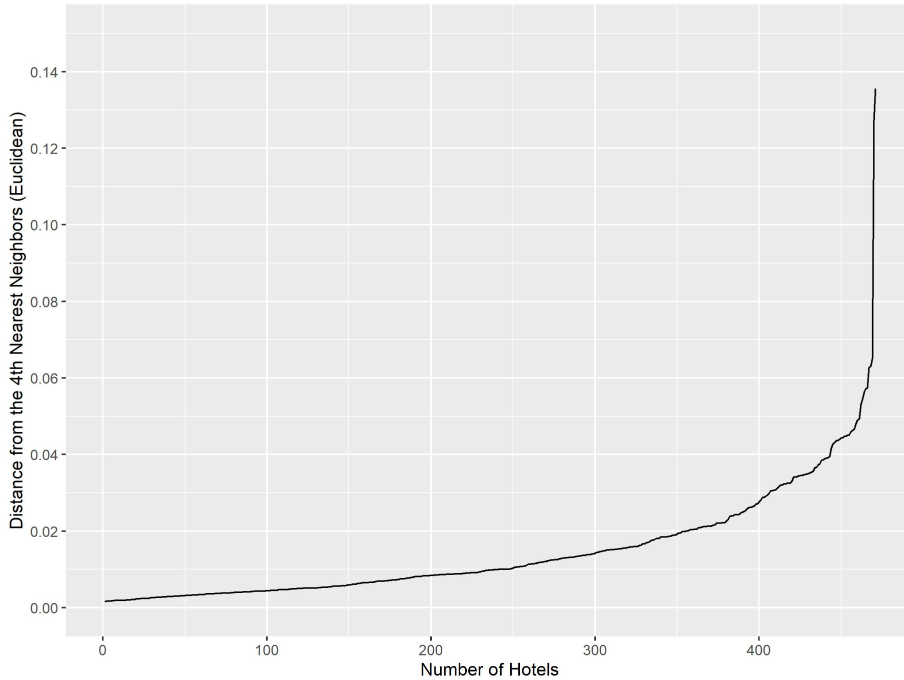


Figure 1: Distribution of Distance from the Fourth Nearest Neighbor (2014 Q1)

The results of the clustering are summarized in Figure 2. The algorithm produces 21 clusters, with 359 observations for four quarters (Around 90 observations per quarter) considered as noise points (and excluded from the reduced form and structural models analyses).

3.3 Measures of Multimarket Contact

The structural and reduced form models require different measures of MMC. The structural approach models MMC for each hotel pair, whereas, as already explained, the reduced form approach analyzes a firm's "aggregated" MMC across all the competitors it faces.[9] Consequently, this paper uses two measures of MMC: 1) a firm-specific (aggregate) measure ($AMMC_j^m$) and 2) a hotel-pair-specific measure (MMC_{jk}^m; henceforth "pair-specific" measure). The firm-specific measure is well-suited for the reduced form model whereas the pair-specific measure is used in the structural approach.

The two measures are related: we obtain the firm-specific measure by summing over a firm's pair-specific measures in a market. We describe both measures next.[10]

[9]As stated earlier, because of this difference, the structural model is able to incorporate MMC more precisely and measure its effect more accurately.

[10]As stated earlier, we carry out a robustness check for the reduced form regressions, in which we use an alternative method of delineating markets. See Appendix B for further details.

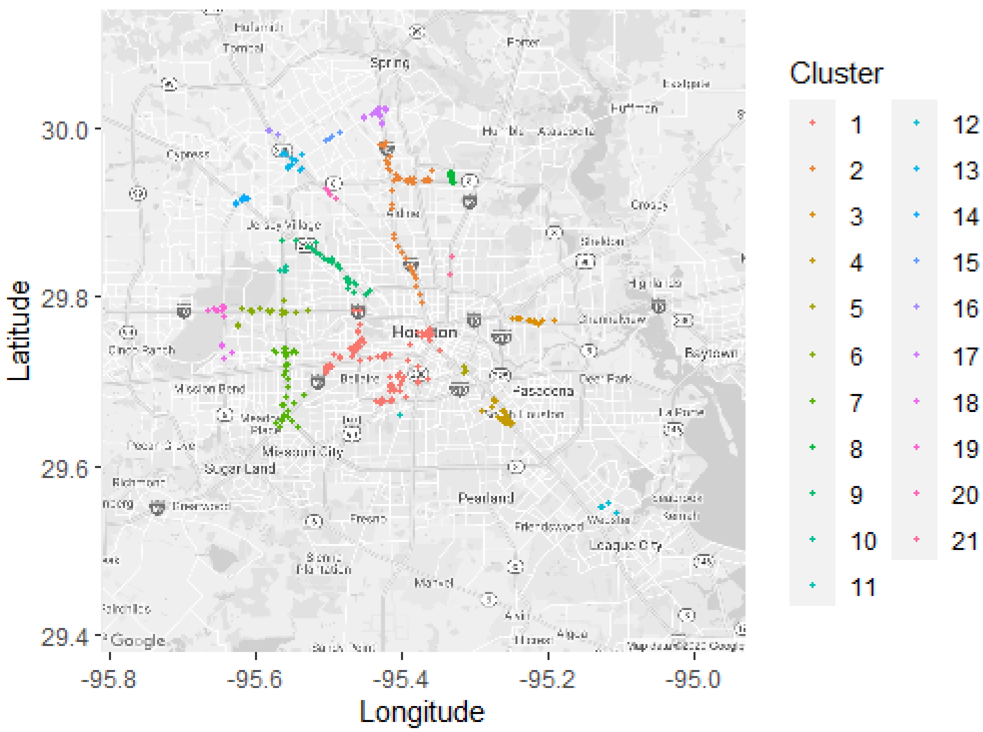


Figure 2: Clusters of Houston, TX (2014 Q1)

3.3.1 Pair-Specific Measure of MMC

The pair-specific measure of MMC between firms j and k in market m ($j, k \in F^m$; F^m is a set of firms in market m) is as follows

$$MMC_{jk}^{m} = \frac{\sum_{m' \neq m} I_j^{m'} \cdot I_k^{m'}}{\sum_{m'} I_j^{m'}} \tag{3}$$

where I_j^m ($I_j^{m\prime}$) equals one if firm j is present in market m (m'). Otherwise, this is equal to zero. MMC_{jk}^m is standardized by the number of markets in which firm j is present ($\sum_{m'} I_j^{m'}$). With this measure, we can construct matrices of all hotel-pair MMC for all markets, including the ones with branded and non-branded hotels.

3.3.2 Firm-Specific (Aggregate) Measure of MMC

In line with prior work (Silva, 2015; Gimeno and Woo, 1996; Evans and Kessides, 1994), we use the sum of the pair-specific MMC across rivals. The aggregate multimarket contact of firm j in market $m = 1, \cdots, M$ facing rivals $k \in F^m, j \neq k$ is:

$$AMMC_j^m = \sum_{k \neq j}^{F^m} MMC_{jk}^m. \quad (4)$$

We note that none of the independent hotels in our data operate units across markets. As a consequence, independent hotels have measures of MMC (MMC_{jk}, and $AMMC_j$) equal to zero. Independent hotels, however, are included when defining markets and in the estimation of the reduced form model and in the structural analysis. Further, consistent with prior literature (Fernandez and Marin, 1998; Silva, 2015), we define firms (i.e. j, k) at the brand level (e.g., Four Points, Courtyard), rather than at the chain level (i.e., Marriott).

3.4 Descriptive Statistics

Table 1 displays descriptive statistics. The top panel shows the main variables whereas the bottom panel shows the MMC measures.

As mentioned earlier, the MMC for independent hotels is equal to zero. Thus, the table separately reports the MMC measure for the subset of branded hotels. Figure 3 shows the distribution of MMC_{jk} for branded hotels.

Table 1: Descriptive Statistics of Key Variables

Var.	N	Mean	St. Dev.	Min	Max
Price	1,521[1]	92.047	53.117	17.82	400.75
Share(s_j)	1,521	0.038	0.06	0.001	0.615
Rating	1,521	1.987	1.6587	0	6
No. of Rooms	1,521	125.949	122.84	27	1200
No. of Activities	1,521	2.269	2.669	0	7
No. of Room Amenities	1,521	3.382	2.423	1	9
No. of Room Types	1,521	1.409	1.259	0	3
No. of Services	1,521	3.317	2.903	1	12
HHI[2]	1,521	0.069	0.065	0.022	0.320
MMC_{jk}					
All hotels[3]	40,814	0.164	0.265	0.000	1.000
Branded hotels	14,696	0.456	0.250	0.091	1.000
$AMMC_j$	1,521	1.009	0.857	0.0000	3.571

1: Noise observations are dropped though DBSCAN.

2: HHI represents the capacity-based Herfindahl index.

3: Independent hotels are assumed to have no MMC with other hotels.

Price is measured as the average daily room rate. The variation of the average rate is high since our sample includes all levels of hotels, from *Economy* to *Luxury*. Share is measured as the number of rooms sold by a hotel divided by the total number of available rooms in the market. The distribution of shares is wide since some markets have many hotels while some markets have few competitors. This range results from the application of the clustering algorithm used to define the market.

Hotel rating represents overall hotel product quality (at the brand level), as measured are by *Smith Travel Research Inc.* Since non-branded hotels are not part of this rating scale, these units are assigned a value of zero for this variable. This is an arbitrary choice since some independent hotels could be considered, for example, upscale or luxury. Thus, the rating variable is only used in the descriptive (reduced form) analysis. The structural analysis uses, instead, hotel characteristics.

The number of activities represents the facilities or features, other than accommodation, available at the hotel. These activities include: restaurants, bar, pools, gyms, and kids activities. The reason of defining a variable in this way is to include product characteristics in a more parsimonious fashion.

The number of room amenities is the sum of room features, including air conditioning, room services, mini bar, refrigerator, and other amenities in the hotel room. The number of room types represents how many room types a hotel provides (e.g. singles, doubles, and suites). The number of services is the sum of general services in the hotel, including concierge, shuttle bus, front desk, etc. HHI represents the Herfindal Index based on the number of available room of the hotels in the market.

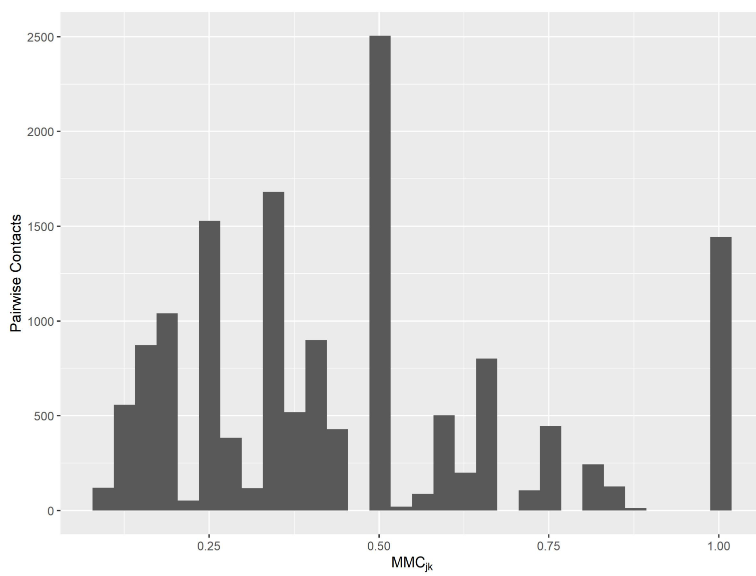


Figure 3: Distribution of MMC_{jk} for Branded Hotels

4 Model and Estimation Details

4.1 Reduced Form Model

We follow prior literature and regresses price on a measure of multimarket contact ($AMMC_j^m$) and product characteristics (X_j):

$$P_j^{mt} = \alpha_1 AMMC_j^{mt} + \beta X_j^{mt} + \nu_j^{mt} \tag{5}$$

where X_j^{mt} represents product characteristics of firm j in market m at period t (including the number of rooms and hotel ratings). In addition, we include the HHI concentration measure, as well as non-branded and chain fixed effects. Similar to prior studies (Fernandez and Marin, 1998; Silva, 2015), the fixed effects are included to mitigate issues arising from the possible endogeneity of MMC measure. Despite this attempt to make this model more causal, we state at the outset that we regard the reduced form model as descriptive and only suggestive of the likely causal relationship between MMC and prices. Further, as we already explained, the reduced form approach is limited to an aggregate (firm-level) measure of MMC, while MMC is pair-specific in nature. The structural model, which we explain next, is better suited to address these shortcomings.

4.2 Structural Model

4.2.1 Demand Side

We adopt a nested logit demand model where products are grouped in mutually exclusive categories. Each category (or "nest") is denoted by g ($g = 0, 1, \cdots, G$; $g = 0$ represents the outside good). The nests in this paper are hotel qualities based on the standard hotel rating system.[11] The indirect utility of consumer i, for product j in market m, is given by:

$$\begin{aligned} u_{ij}^m &= \alpha p_j^m + X_j^m \beta + \xi_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij}^m \\ &= \delta_j^m + \zeta_{ig} + (1-\sigma)\epsilon_{ij}^m \end{aligned} \tag{6}$$

where p_j^m is the average price of product j in market m, X_j^m represents a set of observed product characteristics and ξ_j captures unobserved product characteristics (e.g. product quality). ζ_{ig} is consumer i's utility derived from consuming any product in group (or "nest") g. ϵ_{ij} is a random shock that follows a Type I extreme value distribution.

[11] Three nests (low, medium, and high qualities) are used. The standard hotel rating system is measured by a third-party evaluator, Expedia.com(The standard rating on TripAdvisors.com comes from the evaluation by Expedia.com.

Given the nested structure of the indirect utility function, the (aggregate) probability that consumers choose product j (i.e. product j's market share) is (we omit m for simplicity):

$$s_j = s_{jg} \cdot s_g \tag{7}$$

$$s_{jg} = \frac{\exp(\frac{\delta_j}{1-\sigma})}{\sum_{j \in F_g} \exp(\frac{\delta_j}{1-\sigma})} = \exp(\frac{\delta_j}{1-\sigma})/D_g \tag{8}$$

$$s_g = \frac{D_g^{(1-\sigma)}}{\sum_g D_g^{(1-\sigma)}} \tag{9}$$

where s_{jg} represents the (aggregate) probability that product j is chosen given group g is chosen. s_g indicates the probability that group g is selected. F_g is the set of products in group g. Thus, the market share of product j (s_j) is

$$s_j = s_{jg} \cdot s_g = \frac{\exp(\frac{\delta_j}{1-\sigma})}{D_g^{\sigma}[\sum_{g'} D_{g'}^{(1-\sigma)}]} \tag{10}$$

The specification of the demand side is finalized with the specification of the outside option:

$$s_0 = \frac{1}{\sum_{g'} D_{g'}^{(1-\sigma)}}.$$

Following Berry (1994), the estimable equation for the aggregate market shares is:

$$\ln(s_j) - \ln(s_0) = \alpha p_j + X_j\beta + \sigma \ln(s_{jg}) + \xi_j \tag{11}$$

To deal with the possibility that the unobserved product characteristic ξ_j is correlated with price p_j, we use BLP-style instruments (Berry et al., 1995): the sum of the product characteristics of rivals in the same group (g) as well as the sum of characteristics of hotels in a different group ($g' \neq g$). To estimate demand, we use a generalized method of moments (GMM) estimator based on the following orthogonality condition:

$$g(\theta^d) = E[Z_d\xi]. \tag{12}$$

where $\theta^d = (\alpha, \beta)$. Once demand estimates are obtained, they are used as inputs for the supply side (described next).

4.2.2 Supply Side

We adopt a conduct parameter approach along two dimensions: 1) vertical control and 2) pair-specific MMC. Using different assumptions on these conduct parameters, we create three different models of oligopolistic competition. The baseline (competitive) model (Model 1) assumes that neither vertical control nor MMC exist. Given the estimated demand parameters, firm f (either a franchisor or franchisee) chooses its price of hotel j in a market to maximize its profit (π_f^m).

Model 2 considers full vertical control and allows for pair-specific MMC. In this model, firm f chooses prices of hotels $j' \in F_f$ across all its franchising contracts (F_f is the set of hotels under franchising contracts operated by franchisor firm f) [12]. The underlying assumption in this model is that franchisors exert full control over franchisees' pricing decisions. In addition, profit maximization by a franchisor in this model takes into consideration multimarket contacts with competitors.

Model 3 is similar to model 2 but it relaxes the assumption of full vertical control: franchisor f has partial control over hotels ($j' \in F_f$) under its franchising system. To operationalize the notion of partial control, we introduce a parameter (between 0 and 1) that we take to estimation. A value of zero for this parameter implies complete independence of the franchisee to make pricing decisions; a value of one implies full vertical control (as imposed by model 2).

In the same vein, to implement the notion of MMC in models 2 and 3, we estimate a parameter that measures the degree to which firms incorporate MMC in their pricing decisions (a value of zero in this parameter implies that MMC is irrelevant whereas a value of 1 implies that MMC is fully considered).

Specifically, the profit function that nests our three models is given by:

$$\begin{aligned}\pi_f^m = &\underbrace{(p_j^m - mc_j^m)s_j^m M^m}_{\text{Own (Single-Unit) Profits}} \\ &+ \underbrace{\sum_{j' \in F_f} f_{vc}(I_{jj'}; \lambda_{vc})(p_{j'}^m - mc_{j'}^m)s_{j'}^m M_m}_{\text{Consideration of Vertical Control}} \\ &+ \underbrace{\sum_{k \neq j,j'} f_{mmc}(MMC_{jk}; \lambda_{mmc})(p_k^m - mc_k^m)s_k^m M_m}_{\text{Consideration of MMC}} \qquad (13)\end{aligned}$$

where mc_j^m is product j's marginal costs in market m, and M^m represents market market m's market size. $I_{jj'}$ is an indicator variable that is equal to 1 if firms j and j' belong to franchisor f. $f_{vc}(I_{jj'}; \lambda_{vc})$ is a function with parameter λ_{vc} that maps $I_{jj'}$

[12] in our data, hotels that do not have franchising contracts (i.e. independent hotels, simply maximize profits for that unit alone

onto the $[0, 1]$ interval while $f_{mmc}(MMC_{jk}; \lambda_{mmc})$ is a function with parameter λ_{mmc} that maps MMC_{jk} (as described earlier) onto the unit interval.

The profit function has three components. The first component (Own Profits) captures the profit of a single hotel. The second component captures the portfolio effect derived from a firm maximizing over a set of owned hotels (Vertical Control). The third term allows for firms to internalize the profit effects derived from facing rival hotels in other markets.

Equation 13 for market m can be written in matrix form as m as:

$$\Pi^m = \Lambda^m (P^m - MC^m) S^m M^m. \tag{14}$$

To illustrate how the three models we consider are mathematically represented in Equation 14, consider an example in which there are three hotels, and hotels 1 and 2 belong to the same franchisor; hotel 3 belongs to a separate franchisor. Then, matrix Λ for each model is presented as follows:

$$\Lambda_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\Lambda_2 = \begin{bmatrix} 1 & 1 & f_{mmc}(MMC_{13}; \lambda_{mmc}) \\ 1 & 1 & f_{mmc}(MMC_{23}; \lambda_{mmc}) \\ f_{mmc}(MMC_{31}; \lambda_{mmc}) & f_{mmc}(MMC_{32}; \lambda_{mmc}) & 1 \end{bmatrix}$$

$$\Lambda_3 = \begin{bmatrix} 1 & f_{vc}(I_{12}; \lambda_{vc}) & f_{mmc}(MMC_{13}; \lambda_{mmc}) \\ f_{vc}(I_{21}; \lambda_{vc}) & 1 & f_{mmc}(MMC_{23}; \lambda_{mmc}) \\ f_{mmc}(MMC_{31}; \lambda_{mmc}) & f_{mmc}(MMC_{32}; \lambda_{mmc}) & 1 \end{bmatrix}$$

where Λ_l $(l = 1, 2, 3)$ represents the profit structure of each specification.

The first order condition of the profit function (Equation 13) is:

$$\begin{aligned} s_j^m + (p_j^m - mc_j^m)\frac{\partial s_j^m}{\partial p_j^m} \\ + \sum_{j'} (p_{j'}^m - mc_{j'}^m)\frac{\partial s_{j'}^m}{\partial p_j^m} f_{vc}(I_{jj' \in F_f}) \\ + \sum_{k} (p_k^m - mc_k^m)\frac{\partial s_k^m}{\partial p_j^m} f_{mmc}(MMC_{jk}) = 0 \end{aligned} \tag{15}$$

Given the demand estimates and the specification of the supply side, marginal costs can be solved for as follows:

$$mc^m(\lambda_{vc}, \lambda_{mmc}) = p^m - \Omega^{-1}(\lambda_{vc}, \lambda_{mmc}) \cdot s^m(\hat{\alpha}, \hat{\beta}) \tag{16}$$

where $\Omega = -\Lambda \cdot \partial s/\partial p$, where $\partial s/\partial p$ is a matrix of derivatives with entry k, j equal to $\frac{\partial s_k^m}{\partial p_j^m}$). In Equation 16 all components are known (prices and shares are observed, and partial derivatives come from demand estimation), except for the conduct parameters. To estimate conduct parameters, we use a GMM approach similar to the one used on the demand side. Specifically, marginal cost for product j in market m is defined as a linear function of cost:

$$mc_j^m = W_j^m \rho + \omega_j^m \tag{17}$$

where W_j^m is a set of cost factors of product j in market m and ω_j^m represents (the unobserved portion of) marginal cost shocks. This reduced form model for marginal costs is used for identifying supply side parameters as well as conduct parameters.

Using Equations 16 and 17, marginal cost shocks are rewritten as follows:

$$\omega_j^m = p_j^m - W_j^m \hat{\rho} - \Omega^{-1}(\lambda_{vc}, \lambda_{mmc}) \cdot \hat{s}_j^m(\hat{\alpha}, \hat{\beta}). \tag{18}$$

In line with prior studies (e.g., Ciliberto and Williams, 2014; Khwaja and Shim, 2017; Michel and Weiergraeber, 2018), we set the following supply moment conditions:

$$g(\theta_s) = E(Z_s \omega) = 0 \tag{19}$$

where $\theta_s = (\lambda_{vc}, \lambda_{mmc}, \rho)$ and Z_s is a set of supply-side instruments.

Identification To estimate the conduct parameters in Equation 19, it is crucial to use a set of instruments that can separately identify markups from unobserved marginal cost shocks. As discussed in Michel and Weiergraeber (2018), valid instruments should be correlated with the endogenous variables (the conduct parameters), while being exogenous to random cost shocks. We use two sets of variables satisfying these two conditions: 1) the numbers of hotels under the same hotel brand in the market and in the city (i.e., how many hotels are operated by a hotel brand) and 2) the numbers of hotels under the hotel chain with which the firm's brand is associated in the market and in the city (i.e., how many hotels of a different brand are operated by the hotel chain with which the hotel is associated).

We argue that a larger presence of hotels of the same hotel brand is a valid instrument as it is likely correlated with markups (and therefore a the conduct parameters). A larger presence of the same branded hotels is a signal of brand visibility in the market (larger demand) and has been show to discourage entry of other branded hotels via spatial preemption (Schmalensee, 1978). Franchisors are likely to add more hotels of the same brand in the market when they expect these benefits and when consumer demand is high. Similar to Kosová et al. (2011), to measure the effect of the presence of the same branded hotels, this paper uses the number of hotels under the same brand in the market and that in the city.

The presence of other hotel brands under the same hotel chain is also likely to be related to markups of all brands under the hotel chain. For instance, chain-level loyalty programs often cover all brands under the same chain. In addition, there can be spillover effects from the hotels with the highest reputation to those less well-known in the chain.[13] Finally, the competitive effects of additional brands under the same chain (intra-chain competition) can be different than those generated if additional brands are introduced by a different chain (inter-chain competition) (Kalnins, 2004; Wilson, 2011). Based on this rationale, our second instrument is the number of hotels within the same hotel chain, excluding the focal brand in the market and in the city.

We argue that the proposed instruments also meet the second requirement for a valid IV (uncorrelated with marginal costs shocks). While our instruments may be correlated with entry/exit decisions of hotel brands (and therefore costs), entry/exit decisions are long-run decisions that are more likely to be related to fixed costs; marginal cost shocks, on the other hand, are likely driven by day-to-day (short-run) idiosyncracies (e.g. managerial decisions).

Additional Details To mitigate misspecification and ease computational burden, demand and supply sides are estimated separately. To estimate the conduct parameters in Equation 13, we use the following specifications:

$$f_{vc}(I_{jj'}; \lambda_v) = \frac{exp(\lambda_v)}{1 + exp(\lambda_v)} I_{jj'} \tag{20}$$

$$f_{mmc}(MMC_{jk}; \lambda_{mmc}) = \frac{exp(\lambda_{mmc})}{1 + exp(\lambda_{mmc})} MMC_{jk}. \tag{21}$$

These specifications restrict the estimated conduct parameters to be on the unit interval ($0 \leq f_{vc} \leq 1; 0 \leq f_{mmc} \leq 1$), as required by economic theory: an off-diagonal element in Λ (see Equation 14) equal to one for f_{vc} denotes full vertical control (zero denotes independence of the franchisee with respect to the franchisor) while an entry of one for f_{mmc} denotes perfect collusion through MMC (zero indicates that MMC is irrelevant for pricing decisions).

5 Results

5.1 Reduced Form

Table 2 reports a battery of OLS results. The first three specifications include non-brand fixed effects: an indicator variable whose value is one if hotels are non-branded. The last three specifications include chain fixed effects. [14] All specifications include

[13] Some hotel brands, such as *Courtyard by Marriott* and *Four Points by Sheraton*, use the reputation of signature brands in their hotel chains.

[14] Including both fixed effects is unfeasible since non-branded hotels are not chain ones. Thus the chain fixed effects already incorporate the fixed effects of non-branded hotels.

the MMC measure; specifications 2 and 5 add Rating while specifications 3 and 6 include both Rating and HHI. The main takeaway from these results is that there is a robustly positive relation between MMC and prices, a result that is in line with prior findings ((Fernandez and Marin, 1998; Silva, 2015)). These results imply that that an increase of one standard deviation in the level of $AMMC$ (i.e. 0.857), would result in a price increase between \$ 3.749 (4.1%) to \$ 6.343 (6.9%).

Table 2: Results of Reduced Form Model

	Dependent Variable:					
	Price					
	(1)	(2)	(3)	(4)	(5)	(6)
MMC	4.374**	7.395***	7.401***	3.133*	5.015***	5.007***
	(2.080)	(1.530)	(1.530)	(1.850)	(1.729)	(1.729)
Rating		29.164***	29.153***		25.248***	25.234***
		(0.778)	(0.778)		(1.610)	(1.610)
HHI			−12.610			−13.284
			(13.711)			(13.253)
Constant	97.447***	16.918***	18.030***	59.245***	59.245***	60.394***
	(2.554)	(2.851)	(3.097)	(1.678)	(1.564)	(1.939)
Fixed Effects						
Non-Brand	Yes	Yes	Yes	No	No	No
Chain	No	No	No	Yes	Yes	Yes
Observations	1,521	1,521	1,521	1,521	1,521	1,521
R^2	0.138	0.536	0.536	0.510	0.574	0.575
Adjusted R^2	0.137	0.535	0.535	0.502	0.568	0.568
Note:						*p<0.1; **p<0.05; ***p<0.01

5.2 Structural Results

5.2.1 Demand Side

Demand estimates from our preferred specification are summarized in Table 3. All coefficients have the expected sign. Consumers dislike paying high prices and derive a higher utility from more activities (restaurants, pools, bars, meeting facilities, etc.) and services (concierge, shuttle bus, etc.). On average, hotels in downtown Houston are preferred than those near the George Bush Intercontinental Airport.

The chain fixed effects that were included in Table 2 are not included in 3 since these fixed effects may be correlated with other variables, such as the number of activities and the number of services. It is likely that hotel chains or hotel brands keeps the same set of activities or services across their hotels.

Table 3: Results of Demand Estimation

	Dependent Variable:
	$\ln(s_j)$ - $\ln(s_0)$
Price	-0.054^{***}
	(0.004)
No. of Activities	0.344^{***}
	(0.053)
No. of Serivice	0.194^{***}
	(0.043)
Downtown	3.537^{***}
	(0.380)
Airpot	-1.082^{***}
	(0.301)
$\ln(s_{jg})$	0.441^{***}
	(0.092)
Constant	2.055^{***}
	(0.355)
Fixed Effects:	
Quarter	Yes
GMM Objective Values	0.1416
Note:	*p<0.1; **p<0.05; ***p<0.01

We use these demand estimates for the supply-side estimation and the ensuing counterfactual analysis.

5.2.2 Supply Side

Table 4 summarizes the estimates of the supply side for the three models we consider. Consistent with expectations, results indicate that the marginal cost of providing a hotel room increases with the number of room amenities and the number of services. Also, larger hotels exhibit greater marginal costs. While this may seem counterintuitive (i.e. there are no economies of scale), we note that larger hotels usually have higher ratings; one would, thus, expect higher-quality hotels to have larger marginal costs.

Turning to the coefficient on multi-market contact, the results from models 2 and 3 support the view that collusion is facilitated via MMC. Further, the magnitude of this coefficient is greater when the data is allowed to directly speak about the degree of vertical control (model 3) than when full vertical control is assumed (model 2). These results suggest that the effect of MMC would be significantly underestimated if one would impose (the unlikely) restriction that upstream firms have full vertical control of franchisees.

The reason for this is that model 2 fully internalizes the cross-price effects across franchisees, while model 3 only does it partially. Internalizing these cross-price effects in the profit function results in larger equilibrium mark-ups. In order to rationalize these larger (implied) mark-ups with the observed data, the model rescales the MMC coefficient downward. Model 3, on the other hand, implies smaller mark-ups because the cross-price effects are only partially internalized in the profit maximization process thereby resulting in a larger effect of MMC.

Table 4: Results of Supply Side Estimation

	Dependent Variable:		
	Marginal Cost		
	Model 1	Model 2	Model 3
λ_{vc}			-1.5779**
			(0.7326)
λ_{mmc}		0.2004***	3.1461***
		(0.0019)	(0.1726)
Constant	29.0312***	32.3508***	34.1011***
	(3.3025)	(0.0915)	(0.1044)
No. of Rooms	0.2676***	0.1739***	0.2061***
	(0.0277)	(0.0008)	(0.0008)
No. of Room Amenities	4.7218***	2.5025***	5.1567***
	(0.7446)	(0.0187)	(0.0195)
No. of Room Types	-0.3535	-4.409***	-0.289***
	(1.5239)	(0.0391)	(0.0498)
No. of Services	1.628**	3.9475***	0.7383***
	(0.8102)	(0.0217)	(0.0218)
Fixed Effects:			
Quarter	Yes	Yes	Yes
GMM Objective Values	110.914	14.2018	98.563
Note:			*p<0.1; **p<0.05; ***p<0.01

We use the estimates from Table 4 to compute the conduct parameters vertical control and MMC conduct parameters as per Equations 20 and 21. Table 5 reports the results. The effect of MMC on prices is 74% larger in model 3 than in model 2 (0.9588 v. 0.5499). Further, model 3 supports the notion that vertical control in the hotel industry exists, but it is only partial. A key takeaway from these results is that models that either neglect vertical control or impose it are likely to produce structural estimates that are biased.

Table 5: Estimated Conduct Parameters

	Model 1	Model 2	Model 3
MMC ($\hat{f}_{mmc}$)	0	$0.5499 \cdot MMC_{jk}$	$0.9588 \cdot MMC_{jk}$
Vertical Control ($\hat{f}_{vc}$)	0	$1 \cdot I_{jj'}$	$0.1711 \cdot I_{jj'}$

5.2.3 Counterfactual Analysis

To quantify the effect of MMC on prices and, we conduct a counterfactual analysis in which the effect of MMC in models 2 and 3 is turned off. Table 6 summarizes how conduct parameters are set up under the counterfactual scenarios.

Table 6: Set Up For Conduct Parameters for Counterfactual Analysis

	Model 2	Model 3
MMC (f_{mmc})	0	0
Vertical Control (f_{vc})	$1 \cdot I_{jj'}$	$0.1711 \cdot I_{jj'}$

Following Nevo (2001), the new equilibrium price under the counterfactual (post) scenario are obtained by using the fixed point iteration:

$$p^* = mc + \Omega^{-1}(p^*)s(\hat{\alpha}, \hat{\beta}, p^*) \tag{22}$$

where the first component in the right hand side, mc, is estimated under the original structure in which MMC does play a role (the "pre scenario").

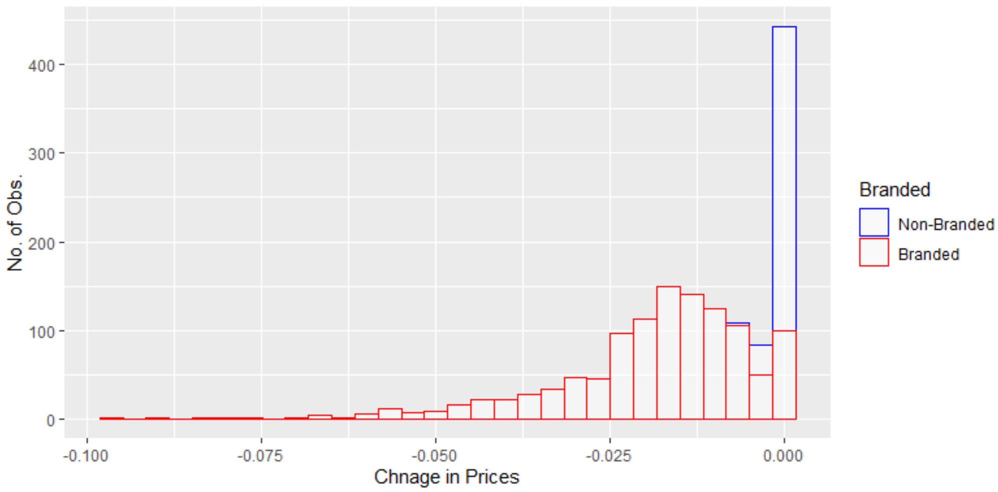
The results of counterfactual analysis are summarized in Table 7. Removing the effect of MMC would decrease prices by approximately 1.4% in model 2 and by 1.54% in model 3. Quantitatively, the effect is in line with what has been reported in prior studies (e.g., Molnar et al., 2013; Khwaja and Shim, 2017). Since MMC occurs only for branded hotels, the effect on non-branded hotels is minimal (see Figure 4. As expected, since MMC has a greater effect on prices in model 3, removal of MMC in model 3 results in a larger (albeit moderately so) price decrease than in model 2.

Table 7: Comparison of Average Observed Prices and Equilibrium Prices

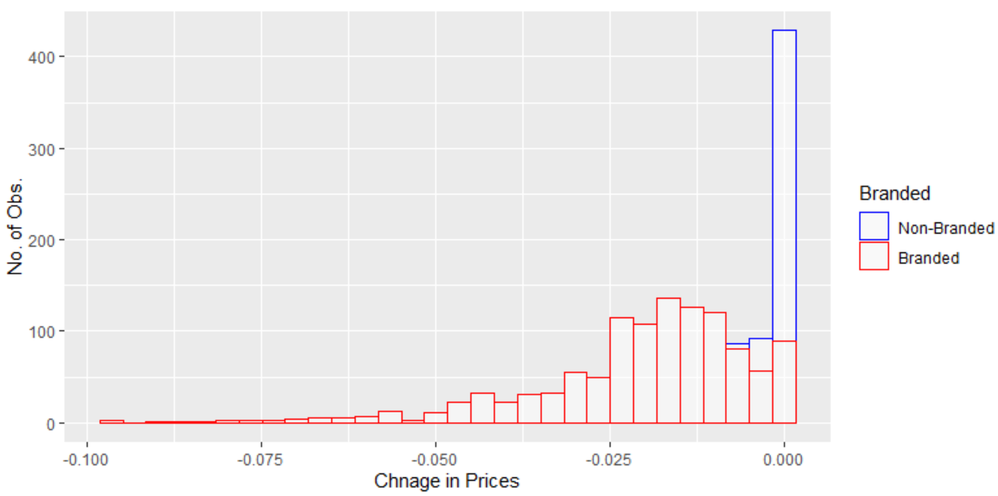
	Observed	Model 2		Model 3	
	p	p^*	% Change	p^*	% Change
Non-Branded	61.79	61.76	0.00%	61.76	0.00%
Branded	102.12	100.59	-1.60%	100.46	-2.00%
All	92.05	90.89	-1.40%	90.79	-1.54%

p: the observed average price

$p*$: the estimated average price



(a) Changes in Price Under Model 2



(b) Change in Prices Under Model 3

Figure 4: Price Changes in the Counterfactual Analysis

6 Conclusion

In this paper, we examine whether MMC, as posed by the BM theoretical model, facilitates collusion in the hotel industry, where hotels face the same rivals in several distinct geographic markets. In line with prior empirical findings, our results confirm that MMC generates supracompetitive prices.

This paper contributes to the literature in two ways. First, we employ a data-driven approach to define geographic markets in an area where no a-priori distinct markets would be identifiable. The approach exploits spatial agglomeration patterns to identify the most likely hotel clusters of competition in the Houston metropolitan area. The defined markets are then used to carry out structural and counterfactual analyses. While our application focuses on a specific industry and area of the country, the approach can be implemented in other industries and geographic areas.

Second, our structural estimation is able to simultaneously consider the effect of MMC as well as that of vertical control. Despite the widespread importance of franchising contracts, prior work on the MMC-price relationship has not considered the role of this vertical aspect of market. Franchising can be thought of as an imperfect substitute for vertical integration, which, in turn, suggests that franchisors may be able to control the downstream price, but only to a certain degree. Our structural model is geared towards quantitatively estimating such degree of partial control. We find, as expected, that franchisors exert partial control over the downstream pricing decisions. To our knowledge, this is the first attempt to empirically quantify the degree to which franchisors exert price control over their franchisees.

Importantly, ignoring the fact that vertical control can only be partial (rather than complete), results in an underestimation of the effect of MMC on prices. The intuition is that a model that assumes full vertical control fully internalizes the cross-price effects across franchisees. This forces the model to (incorrectly) attribute larger mark-ups (and prices) to the internalization of cross-price effects than to MMC. As with our data-driven approach to identify geographic markets, our structural model could be adapted to other industries where vertical contracts (i.e., franchising) are widely used.

This paper has several limitations. First, a hotel brand is considered as a single firm, as have previous studies. However, a single hotel brand is likely to represent just one aspect of the total brand portfolio of a hotel chain. It would be interesting if the existence of multi-branded chains is considered. Second, this paper considers that distance and density are used as the only factors to define markets. Even though this is valid in the sense that hotels tend to share similar product characteristics depending on locations, competition between hotels is realistically limited to hotels of similar ratings. It would be interesting if this type of competition were taken into account.

Appendix

A Analysis of Franchise Disclosure Documents

Franchise disclose documents (FDDs) are sample franchising contracts that franchisors must make available to potential franchisees prior to signing actual contracts. This requirement is mandated and enforced by some state governments and by the Federal Trade Commission. To investigate if franchisors may exercise control over franchisees, we obtained and analyzed franchise disclosure documents of the sample hotel brands in this study. Thes documents were retrieved from the franchise e-filing database of the state of Wisconsin.

Even though the sample of this study is hotels in Houston, Texas, using FDDs fromn the state of Wisconsin is still a pertinent for two reasons. First, most franchisors use uniform franchise contracts for their franchisees (in some cases across countries). Second, the state of Texas does not require filing of FDDs. [15]

The documents reveal three stipulations that may allow franchisors to (partially and/or indirectly) control pricing of franchisees: 1) revenue management systems and consulting services, 2) national/regional marketing by franchisors, and 3) regional/local marketing cooperatives among franchisees.

Revenue management systems and consulting services may facilitate franchisors' control over prices at franchised units. The primary focus of these revenue management systems is to choose the right prices to maximize revenues given market conditions and inventories/demand of individual hotels.[16] To achieve this, the revenue management system collects data, makes forecasts for demand and inventories, and recommend prices for various consumer groups. The systems do not force franchisees to choose specific prices, but can inform them of their suggested prices. Table 8 summarizes the revenue management systems of hotel brands and chains and shows that most franchisors require their franchisees to adopt their revenue management systems. Through these systems, franchisors exert a certain level of control over the pricing policies of their franchisees.

In addition, most franchisors provide consulting services of revenue management for their franchisees, the scope and level of which vary depending on the hotel brands or chains. For example, Red Lion Hotels' *Revenue Management Insight* provides basic market reports covering regional competitors and their pricing. Wyndham has various levels of the consulting services (Platinum, Gold and Diamond) with a mandatory service for opening hotels. These consulting services include basic market reports, and marketing/pricing strategies.

Most consulting services that franchisors offer are mostly optional for franchisees,

[15] Franchisors are asked only to file an exception form under *the Texas Business Opportunity Act*.

[16] Since hotels face higher fixed costs rather than variable costs, maximizing revenues, rather than maximizing profits, has been considered a goal. The term "yield management", often found in the literature and among practitioners, refers to this same notion.

but only sometimes. Most hotel brands require franchisees to use consulting services under the following conditions: 1) if owners are first-time franchisees, 2) if franchisees lack experience or proper personnel to conduct appropriate revenue management, 3) if franchisees are new to hotel brands or related brands, or 4) if franchised units are considered as high quality hotels.[17] The reviewed documents suggest that franchisors have tools at their disposal to influence franchisees' pricing decisions either through mandated or voluntary consulting services.

A second element is national group sales promotions. Most franchisees have options to participate in national or group sales given that prices and quantities are pre-determined by contracts between franchisors and event organizers. Typical examples of these sales are mega sport events or regional conferences (or festivals) in which group sales are determined between hotel national/regional sales managers and event planners. Most hotel brands do not specify these types of sales in FDDs since these sales can be considered as sales supported by franchisors, while Marriott specifies the terms and rules of these sales in its FDDs.

Lastly, franchisees tend to be involved in regional cooperative marketing with other franchisees. Even though most hotel brands indicate that participating in local/regional marketing cooperatives and councils among franchisees is optional, some hotel chains, such as Choice Hotels, IHG, and Wyndham have their own regional cooperatives with financial contributions from franchisees and franchisors. With certain degrees of cooperation between franchisees, or between franchisors and franchisees, franchised units under these cooperative arrangements tend to work as a single firm.

In addition to these three types of the stipulations found in FDDs, franchisors have other options to influence franchisees' pricing policies: management contracts and corporate owned units. Management contracts are a type of vertical contract in which management firms are responsible for operating and managing units, or properties, while owners of the properties play a passive role (exerting less control over their units than typical franchisees). The management firms are responsible for day-to-day and major operations, including pricing and hiring key personnel. Hotel brands or franchisors tend to become management firms, especially for high-quality hotel brands. Moreover, hotel brands/chains own their units under their direct control, called corporate owned units. Through these units, franchisors can determine prices of units under their direct control and can influence pricing of franchised units in their neighborhood.

In sum, since resale price maintenance may be considered a violation of antitrust law, hotel franchisors refrain from directly controlling pricing of franchisees. Instead, franchisors rely on a variety of practices to circumvent this issue and exert certain degree of control over pricing policies of franchisees.

[17] Most hotel chains have uniform policies for revenue management consulting services across their brands, except Hyatt. Hyatt indicates that its mid-price hotel brands, Hyatt House and Hyatt Place, have optional revenue management services while its high-price hotel brand, Hyatt Regency, requires franchisees to use Hyatt's revenue management services.

Table 8: Revenue Management System and Consulting Service

Chain	Brand	Name and Optional(Required)
Best Western	Best Western	Rate Shopping Tool(Required), Property Revenue Management Program(Optional)
Choice	Clarion Comfort Main Stay Sleep Inn Suburban EconoLodge Rode Way Inn	iDeas(Required; a third-party(SAS) revenue management system), ChoiceRM Revenue Management Program(Optional)
ESA	Extended Stay	iDeas (Required)
G6	Motel 6 Studio 6	G6ROW Rate Administration(Required), G6ROW Revenue Optimization(Optional)
Hilton	Doubletree Embassy Hampton Hilton Garden Hilton Home 2 Homewood	QnQ (Required), Revenue Management Consolidated Center(Optional, but required for some cases)
Hyatt	Hyatt House Hyatt Place Hyatt Regency	Hyatt central system (Required), Revenue Optimization Service(Option, but required for Hyatt Regency
IHG	Candlewood Holiday Inn Indigo InterContinental Staybridge Crowne Plaza	IHG Concerto(Required), Yield & Price Optimization(Required), Revenue Management for Hire Service(Optional, but required for some cases)
La Quinta	La Quinta	Revenue Management Services
Marriott	Aloft Courtyard Element Le Merrian Marriot Sheraton Springhill Westin Fairfield Four Points	Revenue Management Advisory Services, Cluster Revenue Management (Both optional, but required for some cases)

Continued from the previous page (Table 8)		
Chain	Brand	Name & Optional(Required)
Radison	Country Inn Park Inn Radison	Revenue Optimization Program (Optional)
Red Lion	Best Value Inn Guest House Knights Inn	IDeas G3(Required), Revenue Management Insight (Optional)
Wyndham	Day Inn Hawthon Howard Microtel Ramada Super 8 Travelodge Wingate Wyndham Garden Wyndham Baymont	Central Rate and Inventory Support Program(Required), Short Term Revenue Management Services(RMS) (Required), Platinum, Gold, and Diamond RMS (Optional)

B Robustness Check of Market Definition: Distance Metric Approach

As an alternative method to define markets for the reduced for analysis, we employ the distance metric approach proposed by Pinkse et al. (2002). The approach is based on the notion of how a competitors react to each others prices in a Bertrand setting with differentiated products. Firms have upward sloping reaction functions, but only if a rival firm is sufficiently close in space. After a certain distance, competitors stop exerting competitive pressure. This distance can be used to empirically define geographic markets. One drawback of the approach is that it will define a market for each hotel which, in turn, does not allow one to have markets that contain mutually exclusive sets of firms (as required by the structural analyses). Thus, we restrict the application of this method to our reduced-form results.

The approach starts with an assumption about competition in the market. Assume that firms in the market play a Bertrand Nash game with differentiated products. In this game, firm j faces the indirect demand function:

$$q_j = a_j + \sum_k \beta_{jk} p_k + \epsilon_j, j, k = 1, \cdots, n \tag{23}$$

where a_j is demand or cost characteristics of firm j. β_{jk} is the price effect on $q_j(\beta_{jj}$ for own-price, β_{jk} for cross-price effects).

The profit function is $\pi_j = p_j q_j = p_j(a_j + \sum_k \beta_{jk} p_k)$. In this equation, the number of parameters to be estimated increases as the number of firms in the market increases. To reduce the number of parameters to be estimated, Pinkse et al. (2002) treat β_{jk} as a function of the distance between firms j and k $(\beta_{jk} = g(d_{jk}))$. From the first order condition and the assumption on β, the price reaction function is as follows:

$$p_j = R(p_{-j}) = \sum \beta x_j^m + g(d_{jk}) p_k + \epsilon_j \tag{24}$$

where x is one of the product characteristics of firm j and ϵ_j is a random shock.

This can be rewritten in a matrix form:

$$P = R(P') = X\beta + GP' + \epsilon \tag{25}$$

$G = g(d_{jk})$ and P' is a cross price matrix with zero diagonal elements. Assume $G = \gamma W$. γ is the only parameter to be estimated and W is a matrix that captures the firm-pair difference in product characteristics. Thus, the price reaction is as follows:

$$P = X\beta + \gamma W P + \epsilon, \tag{26}$$

where

$$G = \gamma W = \gamma \frac{1}{n} \begin{bmatrix} 0 & 1/d_{12} & \cdots & 1/d_{1n} \\ 1/d_{21} & 0 & \cdots & 1/d_{2n} \\ \vdots & \cdots & \ddots & \vdots \\ 1/d_{n1} & \cdots & 1/d_{nn-1} & 0 \end{bmatrix} \tag{27}$$

Once the price reaction is estimated, we use $\hat{\gamma}$ to estimate $\hat{\beta}_{ij}$:

$$\hat{\beta}_{jk} = \hat{\gamma} \frac{1}{d_{jk}} \tag{28}$$

As the distance between firms j and k increases, $\hat{\beta}_{jk}$ approaches zero, indicating that rivals ($k \neq j$) distant from firm k have little effect on firm j's price.

For the estimation of the price reaction function, we use a fixed-effects model. The result is summarized in the following table. The estimate for γ is 0.0016.

Table 9: Price Reaction Function Estimation

	Dependent Variable:
	Price
WP (γ)	0.016***
	(0.002)
Rating	14.611***
	(0.267)
No. of Room	0.059***
	(0.004)
HI Sales	21.025***
	(1.927)
Constant	46.245***
	(3.62)
Fixed Effects	
Quarter	Yes
Observations	1,880
R^2	0.308
Adjusted R^2	0.306
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 5 shows how the cross-price coefficient varies with the pair-specific distance. The effect becomes constant beyond a distance of 2.5 miles or greater. Thus, it is reasonable to assume that rivals more than 2.5 miles from a firm have little effect on the firm's price. This is similar to prior studies in the hotel industry: Vroom and Gimeno (2007) use 2.5 miles as the distance limit.

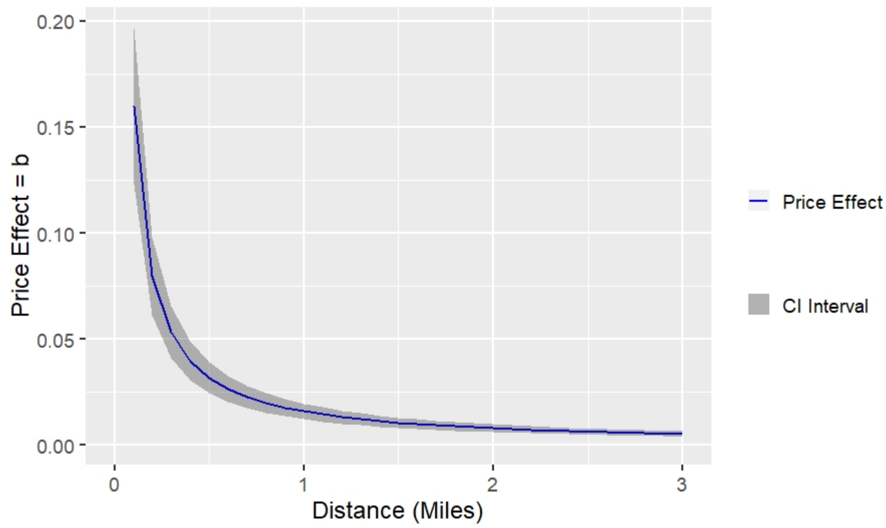


Figure 5: Price Effects (Changes in Distance)

B.1 An Issue with the Distance Metric Approach

Using the 2.5 miles radius, we define a market for each hotel with rivals in its *distance band*. This means a hotel has its own market and this hotel would appear as a rival in its closest rivals' markets. This would create two issues: 1) double counting and 2) indirect effect. The distance band approach assumes that two markets are close–each with some overlap between the markets. In this case, some firms may be counted twice as rivals for both markets. The following figure demonstrates this issue:

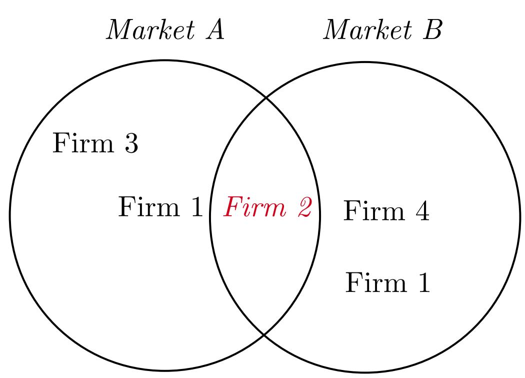


Figure 6: Double Counting

In Figure 6, the left circle represents the market of firm 1; the right circle, the market for firm 4. Texts in the figure represent the location of each firm. Firm 2 belongs to both firm 1's market (the left circle) and firm 4's market(the right circle). Thus, since firm 1 exists in the right circle, firm 2 can be a rival for firm 1 in the right circle. At the same time, firm 2 can be a rival for firm 1 in the left circle.

The second issue is indirect effects. Figure 7 illustrates the indirect effects of a rival that has no direct contact with a firm. The market of firm 4 includes firm 5 that may affect firm 1's behavior through their direct rival, firm 2. This effect may not be negligible since in the hotel industry, a firm's behavior is highly affected by its local rivals.

To deal with this issue, we creates buffer areas for each hotel when calculating multimarket contacts. In the distance band, we exclude hotels whose distance bands are overlapped with a focal distance band.

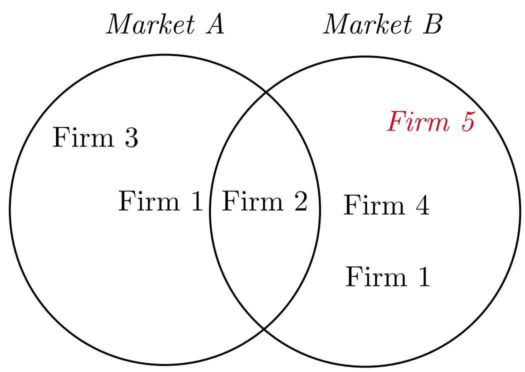


Figure 7: Indirect Effects

B.2 Firm Specific Measures of MMC

Similar to $AMMC$ defined in this paper, we use the following the average measure of the pair-wise MMC:

$$AVMMC_j^m = \frac{\sum_{k \neq j}^{F^m} \sum_{m' \neq m} I_j^{m'} \cdot I_k^{m'}}{N^m - 1} \tag{29}$$

where N^m is the number of firms in market m.

The market definition by the distance metric approach in this study does not create an exclusive market for a firm. This means a firm might appear multiple times when calculating the levels of MMC even though we control for the focal market. Thus, two different measures of $VMMC$ are used to deal with this issue. The method of calculating $VMMC$ is the same in both measures, while these measures are different in recognizing other markets given a focal market.

AVMMC AVMMC considers all possible markets created by the distance metric approach if the firms are sufficiently distant from a focal firm. Figure 8 graphically explains how to calculate AVMMC under the distance band approach. Markets are created by the distance metric approach. Assume that one calculates the multimarket contacts of firm 1 in the left circle. In this approach to AVMMC, this paper assumes

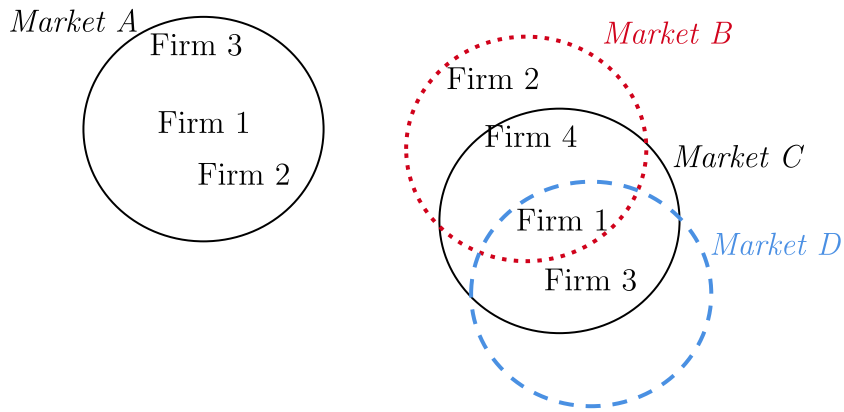


Figure 8: How to Calculate AVMMC

the distance bands of all firms to be independent markets. This means firm 1 appears in the three right circles in Figure 8: Markets B (Firm 4's market), C (Firm 1's second market), and D (Firm 3's market). Thus, there are three other markets. In market B, firm 1 has contact with firm 2, while firm 1 has contact with firm 3 in markets C and D. Thus, the average multimarket contacts for firm 1 in market A are $3/2 = 1.5$ (total number of contacts of rivals in other markets (B,C, and D) / No. of rivals in the focal market (A), AVMMC=1.5).

AVMMC2 Since AVMMC may face issues of double counting in other markets, to circumvent this issues, an alternative counting approach, AVMMC2, is used. In this counting approach, we only consider markets that a firm is a focal firm. For example, when calculating $AVMMC2_i^m$ for firm i in market m, only markets where firm i is the focal firm are considered. Figure 9 graphically explains how to caculate $VMMC2$. Assume we are interested in the $AVMMC2$ of firm 1 in market A. Rather than considering two markets B and D in $AVMMC$, market C (firm 1's second focal market) is treated only as another market for firm 1 in market A. Thus, $AVMMC2$ of firm 1 in market A is 0.5 since firm 1 has a contact only with firm 3 in market C ($AVMMC2 = 0.5$). Thus, with this approach, we can avoid this double-counting issue, especially when firms locate in close geographic areas.

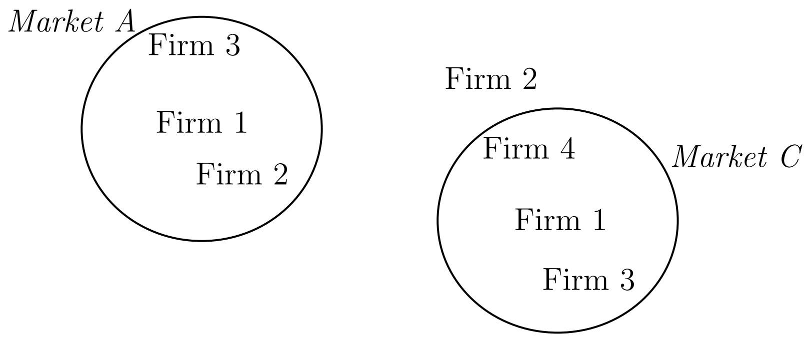


Figure 9: How to Calculate AVMMC2

B.3 Descriptive Statistics of Key Variable Under the Distance Metric Approach

Table 10: Descriptive Statistics of Key Variables

Var.	N	Mean	St. Dev.	Min	Max
Price	1,880	85.849	52.001	118.453	400.75
Rating	1,880	1.763	1.659	0	6
No. of Rooms Sold	1,880	9,460	10,004	11,239	114,480
No. of Rooms	1,880	111.69	117.694	131	1,200
Distance Metric Approach					
No. of Rivals	1,880	20.755	10.918	29	46
AVMMC	1,880	26.689	29.279	46.1	132
AVMMC2	1,880	1.192	1.334	2	9
HHI	1,880	0.138	0.119	0.148	1

B.4 Results of Reduced Form Models

The reduced form models used with these market definitions are similar to the one used in this paper. Tables 11 summarizes the estimation results of the reduced form models with fixed effects. The results from both tables support the view that hotels with more MMC tend to charge higher prices. This means that MMC facilitates collusive behaviors, consistent with prior studies of MMC in the hotel industry (Fernandez and Marin, 1998; Silva, 2015).

Depending on the measures of MMC, the magnitudes of the coefficients of MMC vary, but economic relevance of the effects of MMC is consistent. Thus, we use the standard deviation of the measures of MMC to interpret the meaning of the coefficients of MMC. In Table 11, one standard deviation increase in AVMMC raises prices by $\$2.577 = 0.088 \times 29.279$. Similarly, one standard deviation increase in

Table 11: Estimation Under Distance Metric Approach

	Dependent Variable:	
	Price	
	(1)	(2)
AVMMC	0.088***	
	(0.029)	
AVMMC2		2.788***
		(0.622)
Rating	28.679***	28.799***
	(0.580)	(0.579)
HHI	−29.174***	−31.318***
	(6.679)	(6.666)
Constant	25.308***	23.842***
	(2.282)	(2.255)
Fixed Effects		
Chain	Yes	Yes
Observations	1,274	1,274
R^2	0.665	0.667
Adjusted R^2	0.664	0.667
Note:	*p<0.1; **p<0.05; ***p<0.01	

AVMMC2 makes prices higher by \$3.719 = 2.788×1.334. Both cases show similar increased prices due to one standard deviation increases in the measures of MMC.

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