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. Since these studies in this category use reduced form models to exam the relationship between MMC and price, or other product characteristics, it is required to set up one-to-one correspondence between dependent variables, prices, and a variable capturing the level of MMC, either the market level of MMC over all firms in the market or the firm level of MMC over competitors in the market. Even though a firm face different competitors, creating multiple dimensions of MMC for each competitor, the reduced form models cannot capture these dimensionalities of MMC. Structural approaches, reviewed next, do not have this limitation but utilize all firm-pair MMC.

Structural studies rely on the approach introduced by Berry (1994) and Berry et al. (1995). To measure the effect of MMC, studies in this category define conduct parameters as a function of the pair-wise level of MMC between firms, thereby incorporating all MMC relationships between a firm and its competitors. An additional advantage of these studies is that counterfactual or welfare analyses can be carried out. Ciliberto and Williams (2014) estimate conduct parameters capturing the effect of MMC in the airline industry. The results show 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 market definition. Improperly defined or unjustified market delineations could result in biased estimates. When defining geographic markets, prior work has relied on ad-hoc procedures that are well-justified given the institutional details of the industry being studied. For example, each city-pair route constitutes a distinct geographic market in the airline industry (Evans and Kessides, 1994; Gimeno and Woo, 1996; Ciliberto and Williams, 2014).

In other cases, it is less clear whether the ad-hoc geographic market definitions, although probably reasonable, are the most appropriate. 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 tend to be relatively large thereby resulting in an underestimation of the degree of MMC. 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.[3]

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

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

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 shows 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 that franchisors exert some levels of control over the pricing policies of their franchisees. Finally, we carried out a review of franchise disclosure documents (FDDs) in the hotel industry 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.[4] To summarize, some degree of vertical control in franchising is likely and thus 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. 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*.

3.2 Market Definition: Clustering Approach[5]

Clustering algorithms are one of the non-parametric analyses that groups a set of observations into a cluster that are more closely related to each other than to other observations. 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 for two reasons. First, 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, or avoid arbitrary decisions on clusters (such as the number of clusters).

In clustering through DBSCAN, only two pre-determined parameters are required: the distance limit and the minimum number of nearby points. Given these parameters, DBSCAN identifies core points, points that are surrounded by the minimum

[4]See Appendix A for details of this review

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

number of nearby points within the distance limit. Then, through an iterative process, clusters are determined by including all nearby points (non-core points) within the distance limit. Points 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 distance limit and the minimum number of nearby points) need to be set by the researcher prior to the algorithm applying its iterative clustering procedure. To set a reasonable distance limit, one can use information on the distribution of pair-wise distances between hotels. A distance limit can be set to a level where most of the pair-wise distances are captured. Figure 1 shows the distribution of the distance from the fourth nearest neighbors (4-NN) for each hotel (Euclidean, Miles) in Houston, TX.

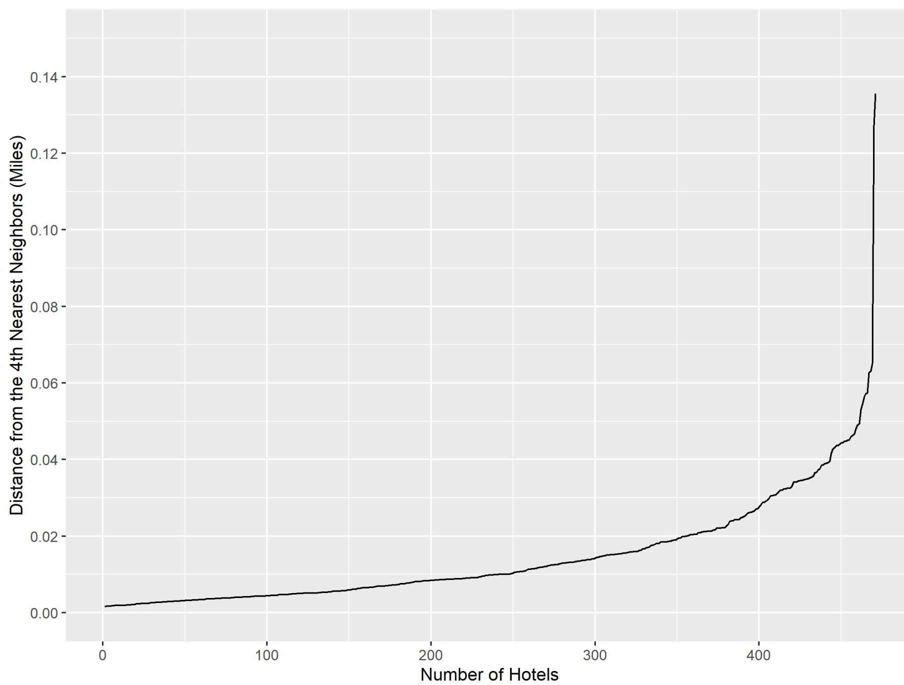


Figure 1: Distribution of Distance from the Fouth Nearest Neighbor (2014 Q1)

Based on the distribution of the distance from the fourth nearest neighbors , this study uses 0.04 miles as the distance limit, as this value captures the large majority of pair-wise distances (94.05%). For the minimum number of nearby points, we checked multiple candidates. Our results use four as the minimum number of nearby points. One reason for using four nearby points is that 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"); the set usually contains the for nearest hotels in the same class (Kalnins, 2006; Rezvani and Rojas, 2020).[6]

[6]Results with different numbers of minimum nearby points (3 and 5 nearby points) are qualita-

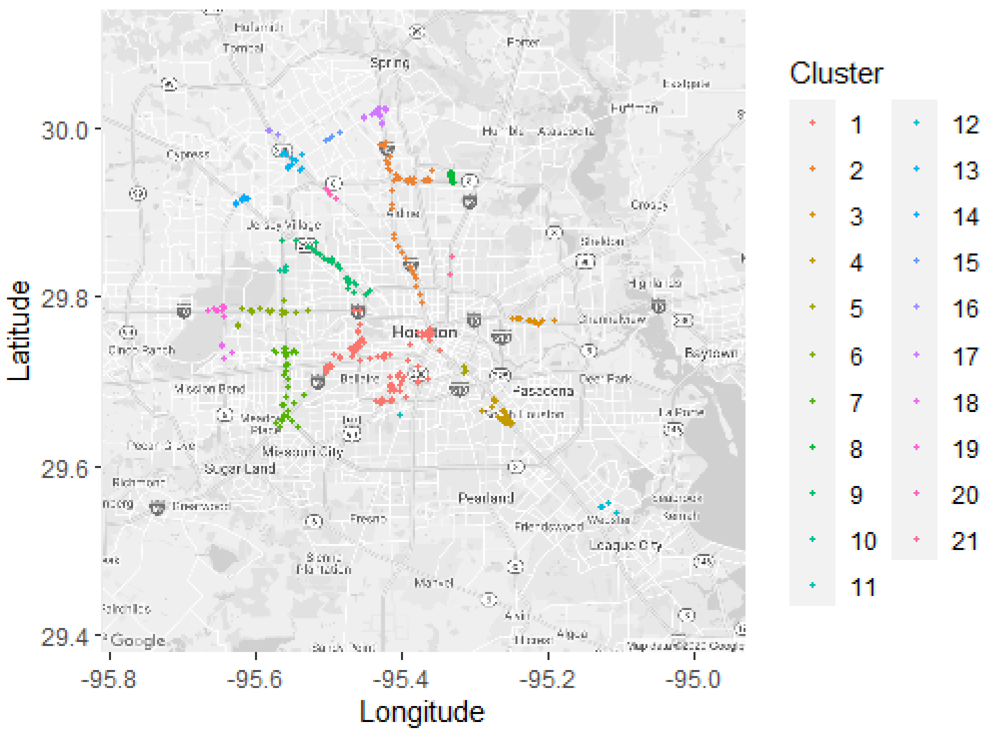


Figure 2: Clusters of Houston, TX (2014 Q1)

The results of the clustering are summarized in Figure 2. For each quarter, 21 clusters are created, while 359 observations are considered as noise points and are excluded from the reduced form and structural models analysis.

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 the reduced form approach analyzes a firm's "aggregated" MMC across all the competitors it faces.[7] 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.[8]

tively similar.

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

[8]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.

3.3.1 Pair-Specific Measure of MMC

The pair-specific measure of MMC between firms j and k at 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 equals one if firm j presents in market m. Otherwise, this is equal to zero. MMC_{jk}^m is standardized by the number of markets in which firm j is present ($\sum_{m'} I_j^{m'}$). This measure incorporates all hotel-pair MMC in the market, including the ones with branded and non-branded hotels.

3.3.2 Firm-Specific Aggregated 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 aggregated multimarket contact of firm j in market $m = 1, \cdots, M$ facing rivals $k \in F^m, j \neq k$ is:

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

Several assumptions are made in calculating MMC_{jk}^m and $AMMC_j^m$. First, since independent hotels are less likely to have multiple hotels across markets, we exclude them in the calculation of MMC while assuming that these hotels have zero values for the measures of MMC (MMC_{jk}, and $AMMC_j$).[9] Independent hotels, however, are included when defining markets and estimating the reduced form model and the demand ans supply sides in the structural model analysis. Second, consistent with prior literature (Fernandez and Marin, 1998; Silva, 2015), we define firms at the brand level (e.g., Four Points, Courtyard), rather than at the chain level (i.e., Marriott).

3.4 Descriptive Statistics

Table 1 shows the descriptive statistics of the variables used in this paper. The top panel shows the variables used whereas the bottom panel shows the MMC measures.

As mentioned earlier, the MMC for independent hotels are assigned a zero; the table, thus, reports the MMC measure separately for branded hotels. Figure 3 shows the distribution of MMC_{jk}. Since non-branded hotels are assumed to have zero multimarket contacts, most observations have zero of MMC_{jk}. However, branded hotels show some levels of MMC_{jk}.

[9] In our data, we do not have any independent hotels operating units across the markets delineated by our clustering procedure.

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	0.080	0.064	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 sales-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 rates is high since our sample includes all levels of hotels from *Economy* to *Luxury* ones. Share is measured as the average number of room sold divided by the total market (the number of rooms available in the market). The distribution of shares is wide since some markets have more hotels while a couple of hotels exist in small markets. This results from the algorithm of DBSCAN that allows to form markets with different numbers of hotels based on distances between hotels and densities of hotels. In addition, the high variation of the number of rooms, representing the capacity, would be another cause.

Hotel rating represents overall hotel product qualities at the brand level that are measured are by *Smith Travel Research Inc.* Since non-branded hotels are not parts of this rating scale, we assign zero for these hotels. This would be arbitrary since some independent hotels could be considered up-scale or luxury ones. Thus, this variable are only included in the preliminary analysis and later replaced with other variables that measures hotel characteristics in the structural model analysis.

The number of activities represents the sum of facilities that serve as other functions rather than accommodation, such as restaurants, bar, pools, gyms, and kid activities. The reason of defining a variable in this way is to reduce the dimensionality of product characteristics. 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 such as 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 sales of the hotels in the market.

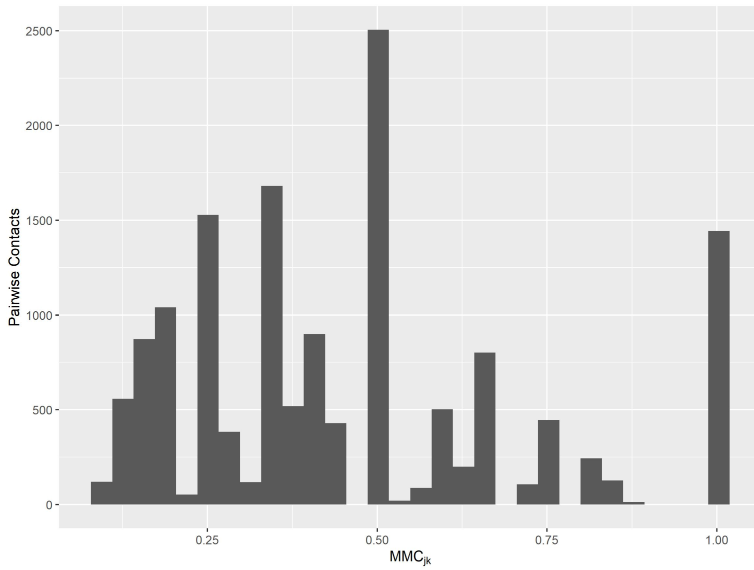


Figure 3: Distribution of MMC_{jk} for Branded Hotels

4 Estimation and Model

4.1 Reduced Form Model

The reduced form model approach is used in this paper to show preliminary results of the relationship between MMC and prices. Prices are assumed to be a function of measures of multimarket contacts ($AMMC_j^m$) 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, and the indicator variables of the presence of a hotel in downtown in Houston or its presence near an airport. In addition, HHI, non-branded and chain fixed effects are included.

Similar to prior studies (Fernandez and Marin, 1998; Silva, 2015), we use the fixed-effect models to deal with the possible endogeneity of the measure of MMC. Even though these are preliminary and descriptive, the main results of this reduced form models in Table 2 confirm the following: hotels with higher MMC tend to charge higher prices, similar to prior studies of MMC in the hotel industry (Fernandez and Marin, 1998; Silva, 2015). This result are also consistent over the models in Table 2.

Table 2: Results of Reduced Form Model

	Dependent Variable:					
	Price					
	(1)	(2)	(3)	(4)	(5)	(6)
AMMC	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

Economically, if the level of $AMMC$ increases by its standard deviation (0.857), the price would increase by \$ 3.749 to \$ 6.343.

4.2 Structural Model Analysis

4.2.1 Demand Side

Consumers i maximize his/her utility to choose product j in market m as follows:

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

where p_j^m is the average price of product j in market m, X_j^m represents a set of observed product characteristics of product j and ξ_j is unobserved product characteristics for product j, such as product qualities. ζ_{ig} is consumer i's common utilities for products in group g ($g = 0, 1, \cdots, G$; $g = 0$ represents outside goods). ϵ_{ij} is a random shock and follows a Type I extreme value distribution.

Given these assumptions on the consumer indirect utility function, the aggregated level of probability that consumers choose product j (equivalent to the market share of product j) in market m (m is excluded in the following notation for convenience) is:

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

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

$$s_g = \frac{D_g^{(1-\sigma)}}{\sum_{g'} D_{g'}^{(1-\sigma)}} \tag{9}$$

where s_{jg} represents the probability that product j is chosen given group g is chosen. s_g indicates the probability that group g is selected. F_g is a 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 definition of outside options:

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

Following Berry (1994), the aggregated level of consumer choices can be estimated:

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

Since the unobserved product characteristics ξ_j (i.e., demand shock) is correlated with price p_j, the instrument variable approach is used. To control for this endogeneity, this paper uses BLP style instruments (Berry et al., 1995): the sum of the product characteristics of rivals in the same group g and those in the different groups $g' \neq g$.

This paper uses the generalized method of moments (GMM) to estimate parameters on the demand side. The moment conditions state that demand shock, ξ is independent of the demand instruments, Z^d:

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

where $\theta^d = (\alpha, \beta)$. The demand side is independently estimated. The estimates in this model are used for further estimations, such as calculation of marginal costs and estimation of the supply side.

4.2.2 Supply Side

On the supply side, this paper considers two aspects of conduct parameters: 1) vertical control and 2) pair-specific MMC. With different assumptions on these conduct parameters, we create three different models of oligopolistic competition. In the competitive model (Model 1: neither vertical control nor pair-specific MMC), given consumer preferences, firm f, either a franchisor or franchisee, chooses its price of hotel j in a market to maximize its profit (π_f^m).

In the full vertical control model(Model 2: full vertical control and pair-specific MMC), firm f, as a franchisor, chooses prices of hotels under its franchising contracts (hotel $j' \in F_f$; F_f is a set of products of firm f) to maximize its profit under consideration of multimarket contacts with competitors (π_f^m). Assume in Model 2 that franchisors exert full control or influence over franchisees' pricing decisions.

In the partial control model(Model 3: partial vertical control and pair-specific MMC), firm f has partial control over hotels ($j' \in F_f$) under its franchising system. Firm f jointly maximizes its profit under partial control over its franchised hotels as well as consideration of multimarkets. Both effects of partial vertical control and pair-specific MMC are empirically estimated within this model.

Thus, the profit function in this paper includes two components of conduct parameters that is discussed in Model 3. Given consumer preferences and characteristics of firms, suppose that firm f chooses prices of hotels under its choice of prices (p_j^m) in market m to maximize its profit with consideration of rivals' profits under vertical control:

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

where mc_j^m is marginal costs of product j in market m, and M^m represents market size in market m. $f_{vc}(I_j; \lambda_{vc})$, a function of $I_{jj'}$ with a parameter $\lambda_{vc}(I_{jj'} = 1$ if firms j and j' are under firm f; Otherwise, it is zero), represents the effect of vertical control. $f_{mmc}(MMC_{jk}; \lambda_{mmc})$ represents the effect of MMC.

Using the matrix form of Equation 13, this profit function for market m can be rewritten as

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

Since this paper estimates several models with different specifications of vertical control and MMC (Model 1 to 3), we use the following example to explain how the conduct parameters are estimated in each model: hotels 1 and 2 under the same firm(franchisor)) and hotel 3 are under the different franchisors. 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 represents the ownership structure of each specification.

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

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

where firms j and j' are under the same upstream firm $f(j, j' \in F_f)$.

Given the demand estimates and the specification of the supply side, marginal costs are defined as

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

where $\Omega = -\Lambda \cdot \partial s/\partial p$ ($\partial s/\partial p$ is a matrix form of $\frac{\partial s_k^m}{\partial p_j^m}$). In this equation, the second element of the right hand side represents markups ($p^m - mc^m()$). Since all elements in Equation 16 are identified (prices and shares are observed, and the partial derivative of shares with respect with prices are estimated in the demand side), only components that need to be estimated are conduct parameters.

To estimate the conduct parameters, we use an approach of GMM similar to the demand side estimation. We specify the marginal costs for product j in market m as a function of cost factors (W_j^m):

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

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

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

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

As prior studies of estimating supply side parameters indicate (e.g., Ciliberto and Williams, 2014; Khwaja and Shim, 2017; Michel and Weiergraeber, 2018), this paper sets the following moment conditions to identify conduct parameters:

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

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

To estimate the conduct parameters in Equation 19, this paper uses a set of instruments that can separately identify markups from unobserved marginal cost shocks. Thus, finding valid instruments is crucial for identifying the conduct parameters. As discussed in Michel and Weiergraeber (2018), valid instruments should be correlated with the endogenous variables(the conduct parameters), while the instruments should be exogenous to random shocks(the marginal cost shocks). This paper uses two sets of variables satisfying these two conditions: 1) the presence of hotels under the same hotel brand (i.e., how many hotels are operated by a hotel brand) and 2) the presence of hotels under the same hotel chain with which the focal firm's brand is associated (i.e., how many hotels of different brands are operated by the same hotel chain with which the hotel is associated).

First, the presence of hotels of the same hotel brand is an valid instrument since this is highly correlated markups. This presence of the same branded hotels creates demand by increasing brand visibility in the market and discouraging entry of other branded hotels via spatial preemption (Schmalensee, 1978). Franchisors (hotel brands) are likely to add more units in the market when they expect these benefits and 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 a focal market and that within a city.

Second, the presence of different hotels hotel brands under the same hotel chain also affects local competition in the market and consequently influences prices and markups of hotels under the same hotel chain. Major hotel chains, such as Marriott, Hilton, Choice, and Hyatt, own and operate more than one hotel brand. For some markets, these hotel chains have more than one unit with different brands associated with their chains. It is reasonable to assume that hotel chains play crucial roles in controlling the entry/exit decisions of each brand in these markets. When considering whether to add additional units into these markets, hotel chains, as joint-profit maximizers, consider the potential effects of intra-chain competition (one between brands in the same chains) and inter-chain competition (one with brands of other chains) (Kalnins, 2004; Wilson, 2011). Especially, the increases in the number of hotel brands under the same hotel chains can reduce competition between their brands, compared to the inter-chain competition (Wilson, 2011). Furthermore, hotel chains also affect demand through chain-level loyalty programs that, in general, cover all brands under the same chain and also through spillover effects from the reputation of the signature brands in the same hotel chain.[10] Thus, this paper uses the numbers of hotels within the same hotel chain, excluding the focal brand in the market and in the city.

These two sets of instruments are considered as exogenous to marginal cost shocks, at least in the short run, even though these may be correlated with entry/exit decisions of hotel brands, or hotel chains. If that is the case, these instruments would be correlated with marginal cost shocks. However, entry/exit decisions are endogenous in the long run of market structure, not in the short run. Pricing decisions of hotels are more frequently made by managers as one of the primarily day-to-day decisions. In addition, entry/exit decisions are more correlated to fixed costs, rather than marginal

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

costs. Thus, the above instruments are valid since the second condition of valid instruments (i.e., exogeneity to random shocks) is satisfied.

This paper estimates the demand and supply sides separately to avoid the influence of misspecification of either demand and supply side models. In addition, this approach does not make an additional assumption of the correlations of the unobserved shocks in demand and supply sides (ξ and ω), while this assumption is commonly used in the joint estimation of demand and supply sides in the structural model.

To estimate the conduct parameters in Equation 13, this paper uses the following specification:

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

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

where $I_{jj'}$ equals one if hotel j and j' are under the same franchisor; otherwise $I_{jj'}$ is zero. MMC_{jk} represents the pair-specific multimarket contacts between j and k. Given those specifications, the estimated conduct parameters are between zero and one($0 \leq f_{vc} \leq 1, 0 \leq f_{mmc} \leq 1$), representing from no-cooperation to collusive conditions. The reason of using the exponential form specification is to ensure the estimated conduct parameters (f_{vc} and f_{mmc}) to be located between zero and one, which is consistent with the assumption of the ownership matrix (Ω) in which the conduct parameters of own products or full control are set to one.

5 Results

5.1 Demand Side

The estimates of the demand side are summarized in Table 3. All signs of the coefficients in the demand side are expected. Consumers dislike paying high prices for staying at hotels. On average, consumer utilities increase as the number of activities, such as restaurants, pools, bars, and meeting facilities, that hotels provides increases. Consumers value the varieties of services provided by hotels, including concierge, and shuttle buses. Consumers staying at hotels in the sample (Houston, TX) prefer hotels in downtown Houston over those at the George Bush Intercontinental Airport.

The demand estimates are used in estimating the supply side and follow-up counterfactual analysis.

5.2 Supply Side

Table 4 summarizes the estimates of the supply side with three different specifications (Model 1 to Model 3). On the cost side, this paper finds that the marginal cost of

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

providing a hotel room increases with increases in the number of room amenities and the number of services in hotels. As the number of rooms increases, so does the marginal cost. This does not support economies of scale largely because the sample of this paper consists of hotels with different ratings. As additional room types are added, costs decrease.

The coefficients related to the effects of MMC (λ_{mmc}) in Models 2 and 3 in Table 4 support the view that firms can facilitate collusion in prices through MMC. The magnitude of this coefficient is greater if the effect of vertical control is simultaneously estimated within a model than if full vertical control is assumed. This result indicates that the effect of MMC would be downward biased if strict vertical control is assumed. In addition, the effects of vertical control and MMC are in a complementary relationship in the influence of collusion on price.

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

Table 5 summarizes the conduct parameters of vertical control and MMC. Considering different specifications for the models, this paper circumvents Corts's criticism (1999) of the estimation of conduct parameters. Two main points can be concluded from this table. First, as mentioned, vertical control and MMC are at a somewhat complementary relationship. The conduct parameters of MMC in Model 3 are larger than those in Model 2, indicating that with partial vertical control, the effect of MMC would increase. Second, this paper empirically estimates the effect of vertical control in hotel franchising. Even though this is limited or may vary with the sample used, this result supports that upstream firms exert a certain level of price control over their downstream firms in a vertical structure or relationship.

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	$1 \cdot I_{jj'}$	$0.1711 \cdot I_{jj'}$

5.3 Counterfactual Analysis

To measure how collusive behaviors via MMC affect consumer welfare, we conduct a counterfactual analysis. The counterfactual scenario is that a government regulation prohibits collusion resulting from MMC, and firms consequently set their prices competitively. Table 6 summarizes how conduct parameters are set up under the counterfactual scenario.

Table 6: Set Up For Conduct Parameters for Counterfactual Analysis

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

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 condition (the pre scenario).

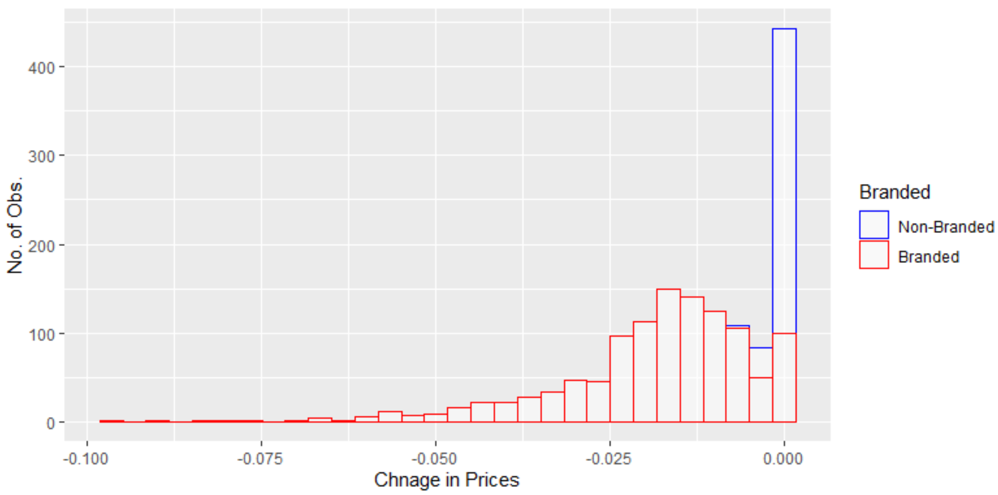
The results of counterfactual analysis are summarized in Table 7. On average, with regulations against collusion via MMC, prices would decrease by approximately 1.4 or 1.54%. While there is little change in prices for non-branded hotels for which this paper assumes no multimarket contacts, the average prices of branded hotels drop under the counterfactual scenario. This result is consistent with prior studies (e.g., Molnar et al., 2013; Khwaja and Shim, 2017).

Figure 4 shows the distribution of price change under the counterfactual analysis. As mentioned earlier, most price changes under the post scenario happen for branded hotels. This results indicate that hotels with high levels of MMC charge high prices, supporting the BM's theoretical framework.

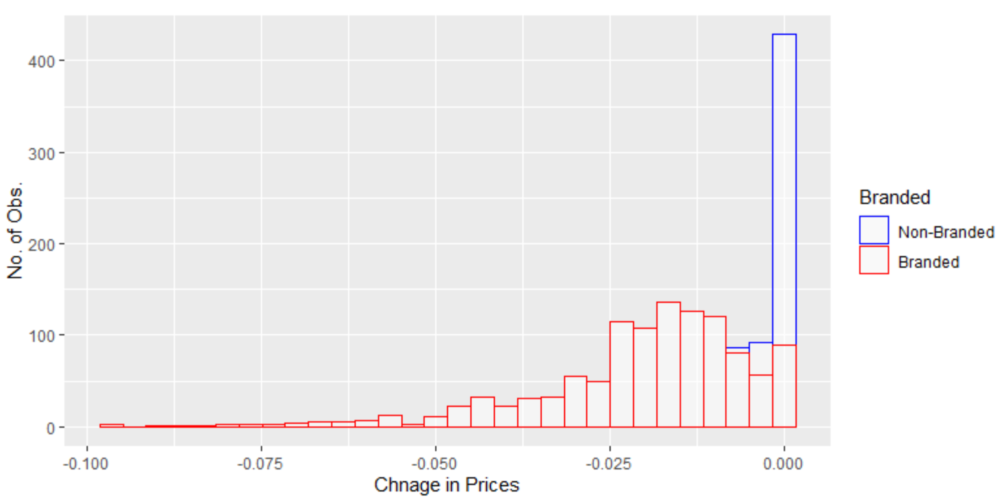
Table 7: Comparison of Average Observed Prices and Equilibrium Prices

	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 examines how MMC facilitates price collision in the hotel industry of Houston, Texas where hotels competes the same rivals over different geographic areas. The results of this paper confirm collusive behaviors through MMC in the hotel industry, consistent with prior empirical studies of MMC and supporting the BM's theortical framework. The contribution of this paper is twofold. First, this paper suggests a data-driven approach to define markets within a metropolitan area that have not been used in prior studies. Competitions of hotels in a metropolitan area provides unique conditions to defining markets: agglomeration, a pattern in which firms locate together. This enables to one of the clustering algorithms, density-based spatial clustering with noises (DBSCAN). With this clustering algorithm, we create mutually exclusive markets and conduct further analysis, such as structural estimation and follow-up counterfactual analysis. This approach can be used in other metropolitan areas in the hotel industry or similar industries.

Second, using the structural model estimation, this paper takes into account two aspects of conduct parameters: 1) MMC and 2) vertical control. Vertical control in the hotel industry plays an crucial role in analyzing firm decisions and competition since most branded hotels are under vertical relationship or contracts, such as franchising. Without the consideration of the effect of vertical control, estimates of the effect of MMC would be biased. To deal with the issue, we take into consideration the effect of vertical control while estimating the effect of MMC. The results of the structural model show that the effect of MMC would be biased without the consideration of the effect of vertical control. This approach of estimating vertical control can be used in other industries where vertical contracts (i.e., franchising) are widely used.

This paper further investigates the impact of MMC on consumer welfare. Counterfactual analysis shows that without collusive behavior via MMC results in the decrease in prices (around 1.5%). Most price decrease happen to most branded hotels with MMC. This result suggests that firm can achieve collusive equilibria through MMC. Even though collusion via MMC is not considered as anti-competitive practices that are prohibited by laws and regulations. However, this should be carefully examined when analyzing potential impacts of merger/acquisition that significantly change the levels of MMC before/after the merger. If that is the case, policy makers should consider the potential effect of MMC on consumer welfare.

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 Disclose Document

Franchise disclose documents (FDDs) are *sample* franchising contracts that franchisors need to make available to potential franchisees prior to signing actual contracts. These requirement are mandated and enforced by some state governments and the Federal Trade Commission. Franchise discourse documents of the sample hotel brands in this study are 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 valid for two reasons. First, most franchisors use uniform franchise contracts for their franchisees, even in foreign countries. Second, the state of Texas does not require filing of FDDs. Franchisors are asked only to file an exception form under *the Texas Business Opportunity Act*.

This study finds three stipulations in the FDDs that may allow franchisors to 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.

First, through revenue management systems and consulting services, franchisors have 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.[11] To achieve this, the revenue management system collects data, makes forecasts for demand and inventories, or 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, but with some exceptions. Most hotel brands require that franchisees use consult-

[11]Since hotels face higher fixed costs rather than variable costs, maximizing revenues has been considered a goal, rather than maximizing profits. Previously, the term yield management was widely used, but revenue management has become more popular among professionals and in academia.

ing 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.[12] Through mandated or voluntary consulting services, franchisors can influence franchisees' pricing decisions.

The second stipulation that franchisors influence franchisees' pricing policies 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, 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 of hotel frnachising, franchisors have other options to control franchisees' pricing policies: management contracts and corporate owned units. Management contracts are a type of vertical contracts in which management firms are responsible for operating and managing units, or properties, while owners of the properties are passive, 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 is considered a violation of antitrust law, hotel franchisors refrain from directly controlling pricing of franchisees. Instead, franchisors use revenue management systems and consulting services to influence franchisees' pricing. In addition, through national/regional group sales, franchisors tend to set prices for these group sales at franchised units even if participation in these sales

[12]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.

is optional. Local marketing cooperative/promotion among franchisees is likely to make franchisees a single entity under these marketing programs. Lastly, franchisors have direct control over pricing at units under management contracts or corporate ownership. This evidence confirms that at a certain level, franchisors have control over pricing policies of franchisees.

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	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)
	Sheraton Springhill Westin Fairfield Four Points	
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 Robust Check of Market Definition: Distance Metric Approach

This paper uses the distance metric approach that is proposed by Pinkse et al. (2002) as an alternative approach to define markets. The distance metric approach is to analyze how a firm is affected by its competitors in setting up its prices in the framework of the Bertrand competition with differentiated products. If a firm consider possible nearby firms within either geographical distances or product spaces as relevant competitors, it responses their firms' action, or prices and vice verse. However, above a certain distance, competitors stop exerting pressure on the firm. Thus, we use the framework of the distance metric approach to empirically define this distance limit. This starts with an assumption about competition in the market. Assume that firms in the market play a Bertrand Nash game using differentiated products. Unlike Bertrand competition with a homogeneous good, firms in this game have market power resulting from product differentiation. 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 this estimation of the price reaction function, this paper uses 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.

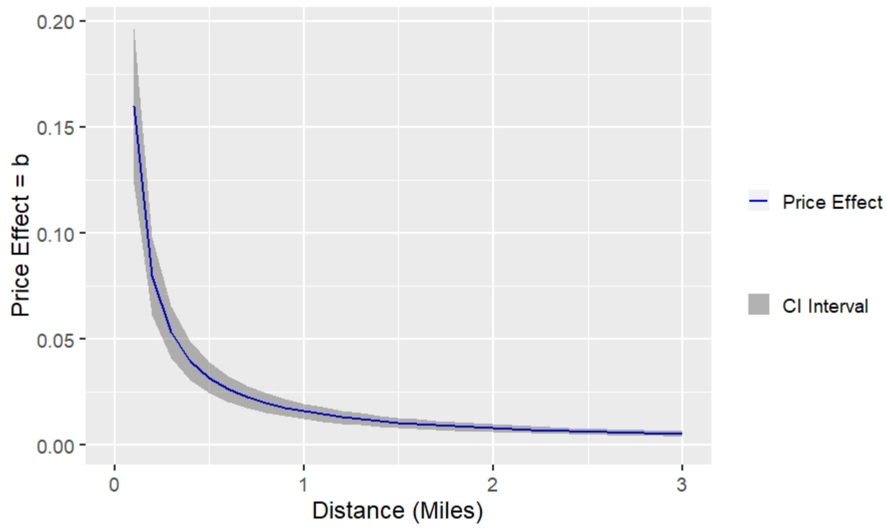


Figure 5: Price Effects (Changes in Distance)

B.1 Issue of Distance Metric Approach

Using estimates (2.5 miles), we define a market for each hotel with rivals in its *distance band*. This means a hotel has its own markets 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:

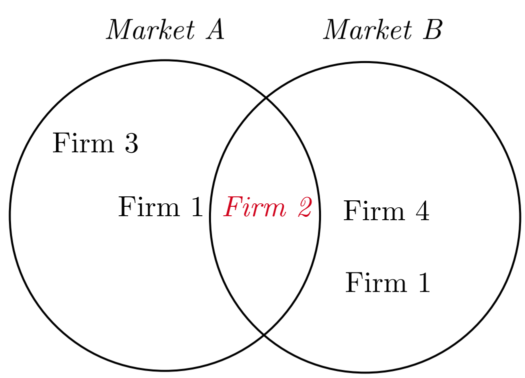


Figure 6: Double Counting

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, indirect effects may create problems. 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 these issues, this paper creates buffer areas for each hotel when calculating multimarket contacts. In the distance band, I exclude hotels whose distance bands are overlapped with a focal distance band.

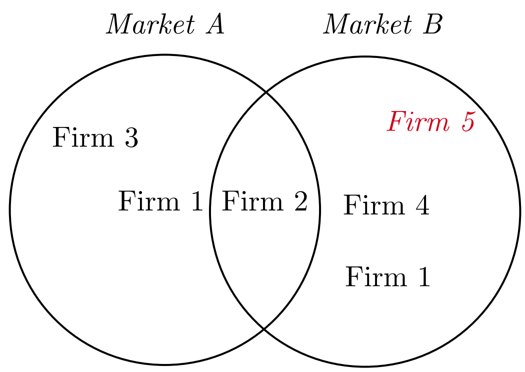


Figure 7: Indirect Effects

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 $AVMMC$ are used to deal with this issue. The method of calculating $AVMMC$ 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

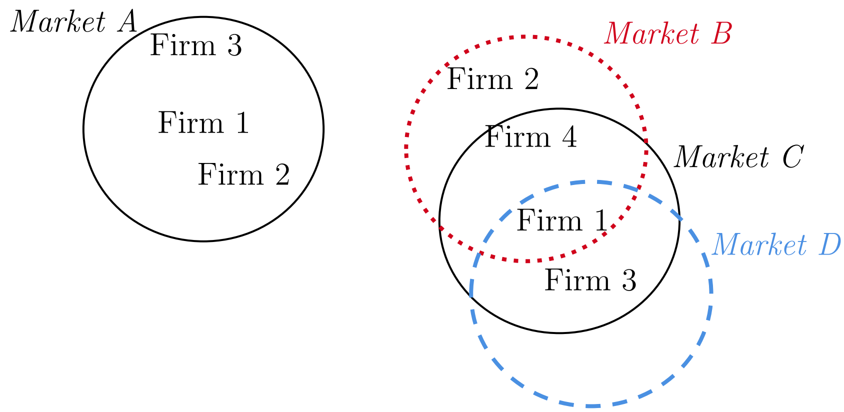


Figure 8: How to Calculate AVMMC

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 $AVMMC2$. 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.

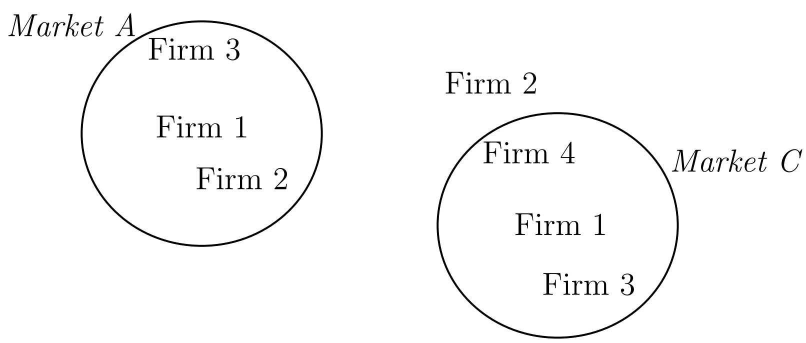


Figure 9: How to Calculate AVMMC2

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 $= 2.788 \times 1.334$. Both cases show similar increased prices due to one standard deviation increases in the measures of MMC.

References

Ater, I. and O. Rigbi (2015). Price control and advertising in franchising chains. *Strategic Management Journal 36*(1), 148–158.

Bernheim, B. D. and M. D. Whinston (1990). Multimarket contact and collusive behavior. *The RAND Journal of Economics*, 1–26.

Berry, S. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, 242–262.

Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, 841–890.

Bilotkach, V. (2011). Multimarket contact and intensity of competition: evidence from an airline merger. *Review of Industrial Organization 38*(1), 95–115.

Ciliberto, F. and J. W. Williams (2014). Does multimarket contact facilitate tacit collusion? inference on conduct parameters in the airline industry. *The RAND Journal of Economics 45*(4), 764–791.

Corts, K. S. (1999). Conduct parameters and the measurement of market power. *Journal of Econometrics 88*(2), 227–250.

Ester, M., H.-P. Kriegel, J. Sander, X. Xu, et al. (1996). A density-based algorithm for discovering clusters in large spatial databases with noise. In *Kdd*, Volume 96, pp. 226–231.

Evans, W. N. and I. N. Kessides (1994). Living by the "golden rule": Multimarket contact in the us airline industry. *The Quarterly Journal of Economics 109*(2), 341–366.

Feinberg, R. M. (2014). Price effects of multimarket contact among movie chains in small us metropolitan areas. *Economics Letters 123*(1), 6–8.

Fernandez, N. and P. L. Marin (1998). Market power and multimarket contact: Some evidence from the spanish hotel industry. *The Journal of Industrial Economics 46*(3), 301–315.

Gimeno, J. and E. Jeong (2001). Multimarket contact: Meaning and measurement at multiple levels of analysis. In *Multiunit organization and multimarket strategy*, pp. 357–408. Emerald Group Publishing Limited.

Gimeno, J. and C. Y. Woo (1996). Hypercompetition in a multimarket environment: The role of strategic similarity and multimarket contact in competitive de-escalation. *Organization science 7*(3), 322–341.

HNN (2012). Brands work to simplify revenue management. *Hotel News Now*.

Jans, I. and D. I. Rosenbaum (1996). Multimarket contact and pricing: Evidence from the us cement industry. *International Journal of Industrial Organization 15*(3), 391–412.

Kalnins, A. (2004). An empirical analysis of territorial encroachment within franchised and company-owned branded chains. *Marketing Science 23*(4), 476–489.

Kalnins, A. (2006). Markets: The us lodging industry. *Journal of Economic Perspectives 20*(4), 203–218.

Khwaja, A. and B. Shim (2017). The collusive effect of multimarket contact on prices: Evidence from retail lumber markets.

Kosová, R., F. Lafontaine, and R. Perrigot (2013). Organizational form and performance: evidence from the hotel industry. *Review of Economics and Statistics 95*(4), 1303–1323.

Kosová, R., F. Lafontaine, and B. Zhao (2011). Scale, scope, ownership changes, and performance. *Available at SSRN 1931021*.

Michel, C. and S. Weiergraeber (2018). Estimating industry conduct in differentiated products markets. Technical report, Working Paper.

Molnar, J., R. Violi, and X. Zhou (2013). Multimarket contact in italian retail banking: Competition and welfare. *International Journal of Industrial Organization 31*(5), 368–381.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica 69*(2), 307–342.

Pinkse, J., M. E. Slade, and C. Brett (2002). Spatial price competition: a semiparametric approach. *Econometrica 70*(3), 1111–1153.

Rezvani, E. and C. Rojas (2020). Spatial price competition in the manhattan hotel market: The role of location, quality, and online reputation. *Managerial and Decision Economics 41*(1), 49–63.

Schmalensee, R. (1978). Entry deterrence in the ready-to-eat breakfast cereal industry. *The Bell Journal of Economics*, 305–327.

Silva, R. (2015). Multimarket contact, differentiation, and prices of chain hotels. *Tourism Management 48*, 305–315.

Vroom, G. and J. Gimeno (2007). Ownership form, managerial incentives, and the intensity of rivalry. *Academy of Management Journal 50*(4), 901–922.

Waldfogel, J. and J. Wulf (2006). Measuring the effect of multimarket contact on competition: Evidence from mergers following radio broadcast ownership deregulation. *The BE Journal of Economic Analysis & Policy 5*(1).

Wilson, N. (2011). Branding, cannibalization, and spatial preemption: An application to the hotel industry. *Federal Trade Commission Bureau of Economics Working Paper* (309).