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

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Abstract

This paper investigates the effect of multimarket contact(MMC) on collusive pricing in the hotel industry where most firms face competitors over geographic markets, even in metropolitan areas. To capture relevant market competition, this paper uses empirical approaches to define markets: a distance metric approach (Pinkse et al., 2002) and a clustering algorithm (Ester et al., 1996). In addition, since most hotels are in vertical contracts, such as franchising, this paper takes into account the vertical control of upstream firms over downstream firms when estimating the effect of MMC on collusive behavior. In this paper, both the effect of vertical control and MMC are simultaneously estimated. The results show that hotels with high levels of multimarket contact tend to cooperate setting higher prices. Using the estimates of the structural model, counterfactual analysis is conducted: absent the extent of collusive behaviors via multimarket contact, prices would be lower by 1.5% to 2%, indicating consumer welfare would be better off the prohibition on collusion through MMC.

1 Introduction

Multimarket contact(MMC) is frequently observed in retail and service industries since firms in these industries compete with their rivals in a series of geographic markets. This inter-firm recognition across markets can create circumstances in which competition between firms could be reduced if behaviors at different markets are coordinated by the internal controls of each firm. Bernheim and Whinston (1990) show theoretically that in a repeated game setting, coordination of firms with multiple contacts create incentives to sustain a collusive equilibrium. This indicates that firms with multimarket contacts tend not to engage in fierce competitions but rather sustain cooperation. Since Bernheim and Whinston (1990), many empirical studies have confirmed the effect of multimarket contacts on collusive pricing in various industries: the airline (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) industries.

This paper is part of the growing empirical literature of multimarket contact and, makes two distinct contributions to the literature. First, it takes into account the extent of vertical contracts that are frequently observed in retail and service industries when estimating the effect of MMC. Among vertical contracts, franchising is one of the most widely used in these industries. To enable coordination via MMC, franchisors(upstream firms) should have control over franchisees (downstream firms) so the franchisors can consider other franchisors' responses in establishing their own prices.[1] Even though franchisors exert strong control over franchisees in various aspects of managerial decisions, it is still uncertain whether franchisors have some level of influence on pricing decisions since direct control by franchisors, known as retail price maintenance, is not permitted in many counties, including the United States. Despite this prohibition, franchisors include various stipulations, either mandatory or voluntary, in franchising contracts to influence franchisees, such as central reservation systems, regional marketing, and group selling with other franchisees. To account for the extent of vertical control, this paper empirically estimates the effects of vertical control when estimating conduct parameters capturing the effect of MMC.

The second contribution of this paper is to propose empirical approaches of establishing a valid market definition that captures competition among firms within a market and isolates this within-market competition from that in other markets. Most studies rely somewhat on geographically isolated markets: metropolitan areas for cement plants within a 200 mile limit, city-route pairs for airlines, and third-party defined tourism areas for hotels. However, these approaches may not be valid for retail or service industries since distribution of firms in these industry are complex. Although firms in these industries are spread widely over regional areas, their distribution shows agglomeration patterns, mostly located close to areas with high demand. To capture distribution, or spatial competition patterns, this paper uses two empirical approaches: 1) a distance matrix approach and 2) a clustering approach. The first approach is based on the framework of Pinkse et al. (2002): firms are likely to respond to geographically closer competitors than others in setting their prices. Using the framework, this paper defines markets with a distance limit and the number of the nearest influential competitors. Second, using a density-based spatial clustering application with noise (DBSCAN), this paper groups firms that are closely located with high densities, while marks as noise firms that are far from the groups. Incorporating these different market definitions makes possible robustness checks of the effect of MMC. These market definitions also provide researchers with flexibility in choosing relevant market definitions depending on their interests of industries, or geographic markets. In addition, these two approaches end up with different types of market definitions. The first approach formulates a market for each firm so reduced

[1] If franchisees set up prices without any influence of their franchisors, cooperation via MMC is highly unlikely since each franchisee is less likely to meet other franchisees in other markets.

form analysis would be valid. On the other hand, DBSCAN allows for defining markets that are mutually exclusive from other markets, enabling further analyses, such as structural estimation and counterfactual analysis (Ciliberto and Williams, 2014; Nevo, 2001; Molnar et al., 2013). Under the first market definition, the distance metric approach, this study finds a 2.5 miles radius as an appropriate distance limit for the distance band approach, similar to prior studies (Vroom and Gimeno, 2007). In addition five neighbors are also identified as influential rivals. This is consistent with a survey of hotel managers conducted by Kalnins (2006). Given these market definitions, this paper estimates the effect of MMC on price and finds a positive correlation between price and the measures of MMC, observing that firms with higher levels of multimarket contact with rivals within an MSA charge higher prices. These results are consistent with prior studies in other industries, such as the airline and cement industries (Evans and Kessides, 1994; Gimeno and Jeong, 2001) as well as in the hotel industry (Fernandez and Marin, 1998; Silva, 2015).

Using the second market definition, the one based on DBSCAN, this paper formulates 21 clusters (markets) for each time period (quarter). Given the defined markets, this paper estimates the structural model of demand and supply sides and finds that the conduct parameter capturing the effect of MMC is positive, indicating that MMC indeed facilitates collusion in pricing. Given the estimates of the structural model, this paper conducts a counterfactual analysis to measure price changes due to collusion via MMC. Without this collusion, prices, on average, would decrease by 1.5%. Even though the estimated welfare (price reduction under the counterfactual scenario) is relatively small, the results are consistent with prior studies that use a structural model (Molnar et al., 2013; Ciliberto and Williams, 2014; Khwaja and Shim, 2017).

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

2 Literature Review

Bernheim and Whinston(1999, hereafter BM) are among the first researchers to propose a theoretical model in which multimarket contact could make collusion feasible in a repeated game setting. In a repeated game, 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 i faces the following incentive compatibility constraint in which a firm chooses to cooperate:

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

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 from cooperation, while the right hand side is the payoff from cooperation.

With multiple markets ($M > 1$), BM argue that pooling the incentive compatibility constraints of each market creates inter-dependency among firms across markets. This means a firm chooses its own price in a market, while considering rivals' responses in the market as well as 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 of MMC, a number of empirical studies examine the effect of MMC on collusive behavior, especially focusing on the relation between MMC and prices in various industries. Even though there are some discrepancies in the results, most empirical studies find supporting evidence for BM's framework that MMC facilitates collusive pricing.

In the literature on MMC, empirical studies can be categorized into two groups depending on what empirical models are used: 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 possible endogeneities of the measures of MMC, the authors use fixed-effects and instrument variable models and find that carriers with high levels of MMC charge higher prices, supporting the theoretical argument of BM. Later studies evaluate interaction effects between other factors and of MMC on price. 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 a demand 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 tend to use reduced form models to exam the relationship between MMC and price, it is required to set up one-to-one correspondence between dependent variables, prices, and a variable capturing the level of MMC, the average 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. Studies in the second category account, however, for the dimensional issues by using a structural model of demand and supply sides.

Studies in the second category rely on the structural model of Berry (1994) or Berry et al. (1995) that estimates demand and supply sides. More specifically, when estimating the supply side, most studies in this category define conduct parameters capturing the effect of MMC as a function of firm-fair measure of MMC, thus utilizing full aspects of MMC that a firm faces in a market. By estimating parameter in this function, the studies can show a relationship between MMC and collusive pricing. In addition, since these studies use the structural models, further analysis, such as counterfactual or welfare analysis is possible.

Ciliberto and Williams (2014), one of the first studies in the second category, use a structural model of demand and supply sides to estimate conduct parameters capturing the effect of MMC in the supply side in the airline industry. The authors incorporate firm-pair specific measures of MMC into the conduct parameter, a function of a firm-pair MMC. This allows firms to consider rivals differently depending on their pair-wise levels of MMC. The results show that airlines presenting in multiple markets sustain collusive equilibrium, indicating that airlines with high levels of MMC charge higher prices. Khwaja and Shim (2017) extend the approach of Ciliberto and Williams (2014) by using a random coefficient model for demand estimation (Berry et al., 1995; **?**). Similar to Ciliberto and Williams (2014), Molnar et al. (2013) examine the effect of MMC in the Italy retail banking industry, especially the deposit side. The results find that banks with high levels of MMC act less competitively than ones with lower MMC.

Regardless of the types of the approaches mentioned above, establishing a valid market definition is one of the initial steps in studies in the literature for estimating the effect of MMC. The market definitions that are used in prior studies vary with sample industries and available data sets. Depending on market definitions, more or fewer firms would be selected in a market. If markets are not well defined, the empirical estimations of the effect of MMC could be biased or become insignificant. Thus, prior studies pay particular attention to define market by considering competition in markets and industry characteristics. For example, studies analyzing the effect of MMC in the airline industry use city-pair routes as a market definition (Evans and Kessides, 1994; Gimeno and Woo, 1996; Ciliberto and Williams, 2014, e.g.,), while 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. Studies of MMC in the hotel industry in Spain use government defined districts based on tourism and business activities to define markets (Fernandez and Marin, 1998; Silva, 2015). However, such market definitions could underestimate measures of MMC since the markets are defined to be relatively large. [2]

Franchising, one of the most widely used vertical contracts, is prevalent in the retail or service industries. Firms, as franchisors, can add more franchised units without significant capital investments, even in an MSA, creating contacts with different franchisors within defined geographic boundaries. However, one might argue that franchisors are not able to control pricing policies of their franchisees since direct price controls by downstream firms (i.e., resale price maintenance) are considered to be illegal. This concern might be mitigated since franchisors are somehow able to control prices of franchisees through their franchise contracts (Moncarz, 1984; Perrigot et al., 2016), nationwide advertising (Ater and Rigbi, 2015), or advanced pricing techniques (HNN, 2012). Also, 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.

More specifically, this paper reviews franchise discourse documents (FDDs), a simple franchising contracts which franchisors provide to potential franchisees before signing actual franchising contracts. FDDs of hotel franchising retrieved from the franchise e-filing database of the state of Wisconsin are analyzed.[3]. This study finds three examples in the FDDs allowing 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 by franchisees (See Appendix for details). Even though these findings are supportive and consistent with prior studies (Moncarz, 1984; Perrigot et al., 2016), it does not guarantee that franchisors have full control over franchisees in pricing.

3 Data

3.1 Data Source

The source of data for this paper is 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 hotel standard ratings, facilities, amenities, and services, are collected from *TripAdvisor*.

[2]Fernandez and Marin (1998) mentions this market definition; 83 markets are identified. Examples of markets are Madrid, Barcelona, and others. Such cities popular with tourists enable hotel brands or hotel chains to have more than one hotel in a city, possibly making measures of MMC lower.

[3]Even though the sample of this study is hotels in Houston, TX, using FDDs from Wisconsin is reasonable 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*

3.2 Market Definition

3.2.1 Distance Metric Approach

This paper uses the distance metric approach to estimate the parameters (distance limit and the Kth nearest neighbor) used to define markets. When estimating the reduced form model and structural models, this paper uses only a sample of hotels in Houston, TX. However, this paper use all hotels in MSA in Texas when estimating of the distance metric model to define market definitions to obtain efficient estimates. The results of the distance metric models with only the Houston hotels are consistent with those in all MSAs in Texas.

Estimation for Distance Limit Based on the framework of distance metric by Pinkse et al. (2002), this paper empirically estimates appropriate 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 the game have market power due to product differentiation. In this game, firm j faces the indirect demand function:

$$q_j = a_j + \sum_k \beta_{jk} p_k + \epsilon_j, j, k = 1, \cdots, n \tag{3}$$

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:

$$p_j = R(p_{-j}) = \sum \beta x_j^m + g(d_{jk}) p_k + \epsilon_j \tag{4}$$

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:

$$P = R(P') = X\beta + GP' + \epsilon \tag{5}$$

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

$$P = X\beta + \gamma W P + \epsilon, \tag{6}$$

where

$$G = \gamma W = \gamma \frac{1}{n} \begin{bmatrix} 0 & 1/d_{12} & \cdots & 1/d_{1n} \\ 1/d_{21} & 0 & \cdots & 1/d_{2n} \\ \vdots & \cdots & \ddots & \vdots \\ 1/d_{n1} & \cdots & 1/d_{nn-1} & 0 \end{bmatrix} \tag{7}$$

Once the price reaction is estimated, I use $\hat{\gamma}$ to estimate b_{ij}:

$$\hat{\beta}_{jk} = \hat{\gamma} \frac{1}{d_{jk}} \tag{8}$$

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 and with the median number of firms (95.624 firms), the cross-price coefficient is 1.530.

Table 1: Price Reaction Function Estimation

	Dep. Var.: ADR	
Var.	Coeff.	C.I (95%)
WP (γ)	0.016***	(0.012, 0.020)
Rating	14.611***	(14.087, 15.135)
No. of Room	0.059***	(0.051, 0.066)
HI (Sales)	21.025***	(17.248, 24.802)
Constant	46.245***	(39.150, 53.340)
Fixed Effect	Quarter, MSA	
Observations	13,868	
R^2(Adj. R^2)	0.308 (0.306)	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Figure 1 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.

Estimation of Kth neighborhood Adopting the distance metric approach by Pinkse et al. (2002), this papers also estimates the Kth nearest neighbor to define appropriate markets. Similar to the first approach, the price reaction function with a distance metric is used. However, W is a matrix of dichotomy values. W includes a certain number of the closest rivals. For example, if there are three closest rivals to be tested, W is

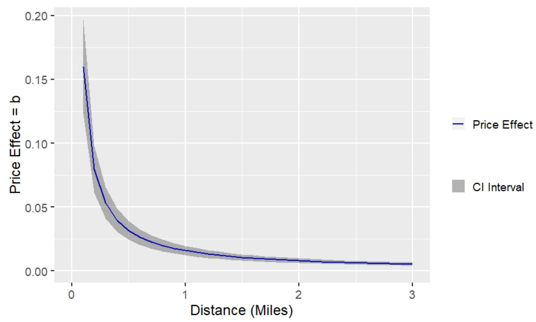


Figure 1: Price Effects (Changes in Distance)

$$W = \begin{bmatrix} 0 & 1 & 1 & 0 & \cdots & 0 \\ 1 & 0 & 1 & 0 & \cdots & 0 \\ 1 & 1 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 0 \end{bmatrix}$$

As the number of nearest neighbors increases (K increases), the price coefficient ($\hat{\gamma}$) will vary. Similar to the approach in the distance band approach, I define a point where the price coefficient remains constant, indicating that adding additional competitions does not change the level of competition.

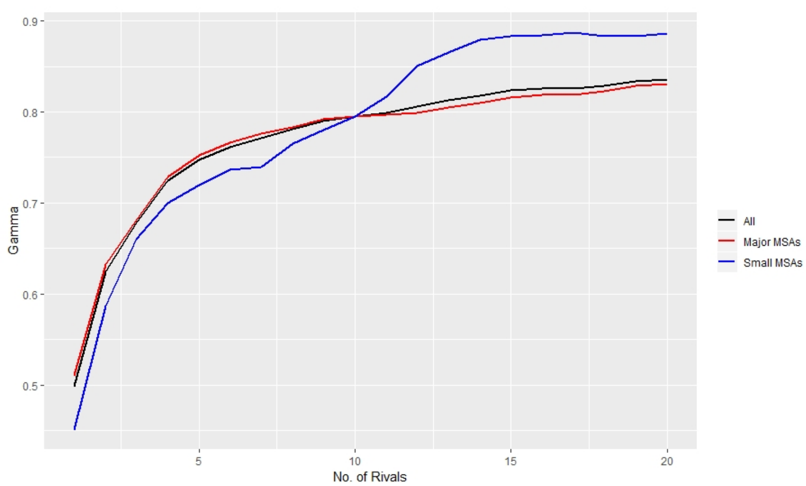


Figure 2: Changes in Price Coefficients with the Number of Neighbors

Figure 2 shows changes in γ, depending on the number of nearest rivals in a matrix W. This shows the price coefficient increases as the number of rivals increases. The coefficient become less responsive to adding an additional rival to W beyond four or five rivals added in W. This paper conservatively uses four as the number of valid neighbors ($K = 4$), which is consistent with prior studies (Kalnins, 2006).

3.2.2 Issue of Market Definition

Using estimates (2.5 miles and 4 nearest neighbors), I define a market for each hotel with rivals in its distance band or with its 4 nearest neighbors in the data set. 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 brand 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.

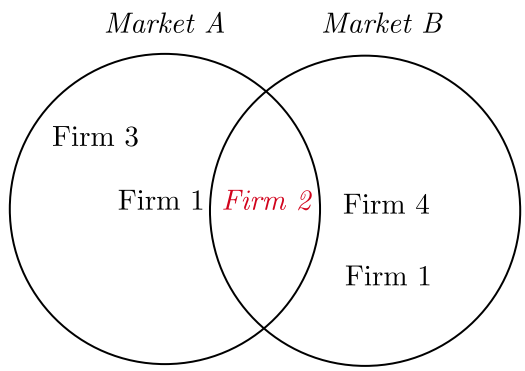


Figure 3: Double Counting

In Figure 3, 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 4 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. Both issues do appear in the K th nearest neighbor approach as well. 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.

For the Kth nearest neighbor approach, I exclude the closet hotels near rivals for a hotel. The procedure is as follows: once firm j is chosen to create a market, its 4 nearest neighbors are selected based on the pair-wise distance (the first degree neighbors for firm j). Each of the first neighbors has its 4 nearest neighbors (the second degree neighbors for firm j). The third degree neighbors for firm j are formed

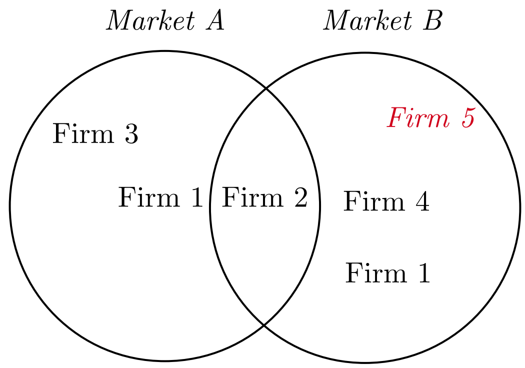


Figure 4: Indirect Effects

as the 4 near nearest neighbors of the second degree neighbors. I exclude the second and third degree neighbors when calculating the level of MMC of firm j. By doing so, I can circumvent both double counting and indirect effect issues.

3.2.3 Clustering Approach

Clustering algorithms are one of the non-parametric analyses grouping a set of observations into a cluster that are more closely related than other observations in other clusters. Among various clustering algorithms, this paper uses the density-based spatial cluster algorithm with noise (DBSCAN) for two reasons (Ester et al., 1996). First, DBSCAN does not require a pre-determined number of clusters. Unlike other clustering algorithms, such as K-mean clustering and hierarchical clustering, DBSCAN can form clusters with little knowledge of markets, or avoid arbitrary decisions on clusters. In the clustering through DBSCAN, only two pre-determined parameters are required, but they are empirically determined: distance limit and minimum number of nearby points. Given these parameters, DBSCAN identifies core points, the ones that are surrounded by the minimum number of nearby points within the distance limit. Otherwise, points are considered as noise points. By iterating this identification process over all observations, DBSCAN identifies a core point as a cluster while nose points are not in any clusters. If a core point locate close with other core points (with the distance limit), these core points, or clusters are combined and considered as a cluster. These two parameters (the distance limit and the minimum number of nearby points) should be determined prior clustering iteration. For example, the distance limit can empirically be determined by analyzing a distribution of pair-wise distances between observations. Choosing a distance limit covering majority pair-wise distances is a way of determining an appropriate limits.

Figure 5 shows the distribution of pair-wise distances between hotels in Houston, TX. The distances are calculated by using Euclidean distance of the latitude and longitude coordinates of hotels.

Based on the distribution of the pair-wise distances, this study uses 0.04 as the

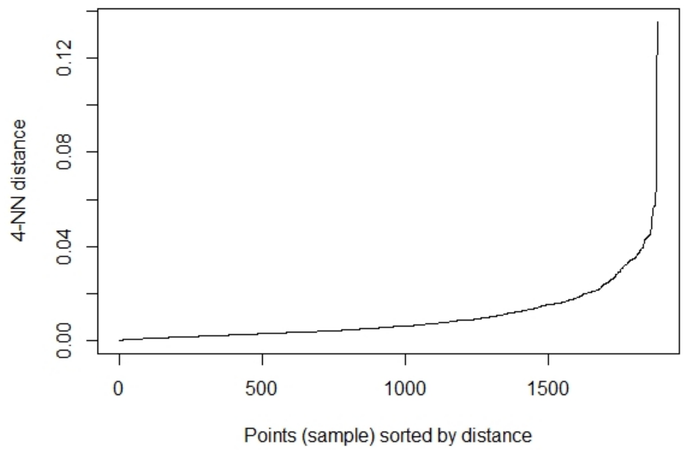


Figure 5: Distribution of Pair-Wise Distances of Q1 in 2014

distance limit and four is the number of nearby points.[4]

The results of the clustering are summarized in Figure 6. In sum, for each quarter, 21 clusters are created, while 359 observations are considered as noise points (excluded from the structural model analysis).

3.3 Measures of Multimarket Contact

This paper uses several measures of MMC: 1) a pair-specific measure of MMC (MMC_{ij}^{m}) and 2) a market-specific average measure of MMC ($AVMMC_{i}^{m}$). The reason of using two different measures of MMC is that each estimation model (the reduced form model and the structural model) requires different measures of MMC. This intuition of using these different measures is that a firm facing a set of competitors in a market have contracts with those competitors in other markets. Since all firms do not equivalently present in all markets, a firm could have different contacts with different competitors. Thus, the pair-specific measure of MMC captures variation of MMC, enabling to estimate realistic effects of MMC through the structural model and further counterfactual analysis.

Second, the firm-specific average measure of MMC is suitable for the reduced form analysis for both market definitions (distance-metric approach and clustering approach) since the reduced form model analysis requires one-to-one correspondences between a dependent variable and an independent variable. Thus, the measures of MMC should be summarized into a single variable. This paper uses the firm-

[4]To find out appropriate number of nearby points, this study checks multiple candidates: four and five points. The results are consistent.

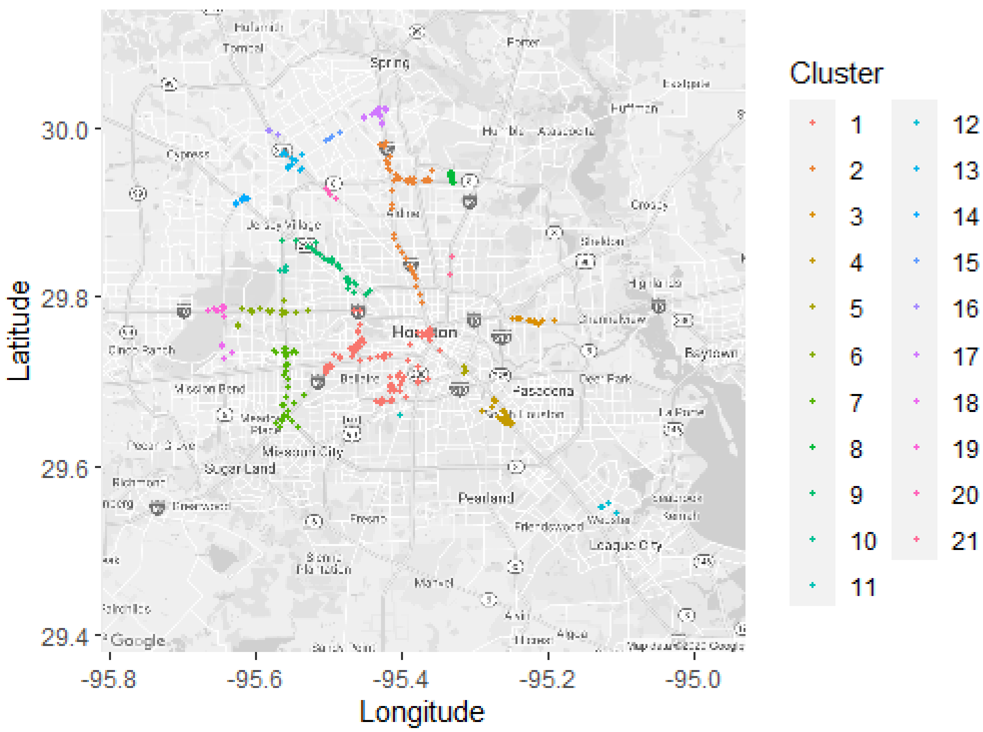


Figure 6: Clusters of Houston, TX (2014 Q1)

specific average measure by averaging pair-specific measures of a firm over all other competitors in a market.

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

$$MMC_{jk}^{m} = \frac{\sum_{m' \neq m} I_j^{m'} \cdot I_k^{m'}}{\sum_{m'} I_j^{m'}} \tag{9}$$

where I_j^m equals one if firm j presents in market m. Otherwise, this is equal to zero. Since MMC_{jk}^m is standardized by dividing the number of markets in which firm j presents ($\sum_{m'} I_j^{m'}$).

3.3.2 Firm-Specific Average Measure of MMC

Since this paper uses reduced form models for preliminary analysis and robust checks of different market definition, it is required to set up one-to-one relationship between price (dependent variable) and and measure of MMC(indepedent variable). Thus, the measures of MMC should be the average of MMC across rivals in a market for the reduced form model, similar to Silva (2015); Gimeno and Woo (1996); Evans and Kessides (1994). It sdf The average multimarket contact of firm i in market $m = 1, \cdots, M$ with rival $k \in F^m, j \neq k$ is:

$$AVMMC_j^m = \frac{\sum_{m' \neq m} I_j^{m'} \cdot I_k^{m'}}{N^m - 1} \tag{10}$$

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

As mentioned earlier, this definition of MMC is primarily used under the distance metric market definition, while the pair-specific measure of MMC is used for the structural model analysis with the clustering market definition. Table 2 summarizes the market and MMC definition along with the estimation model.

Table 2: Estimation Strategy Under Market and MMC Definitions

		Market Definition	
		Distance Metric	Clustering
MMC Definition	Pair-Specific		Structural Model
	Firm-Specific	Reduced Form	

The distance metric market definition 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 I control for the focal market. Thus, two different measures of AVMMC are used to deal with this issue. The method of calculating the level of MMC 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 band or the Kth nearest neighbors approach if the firms are sufficiently distant from a focal firm. Figure 7 graphically explains how to calculate AVMMC under the distance band approach. Markets are created by the distance band approach, but this logic may also apply for the Kth nearest neighbor approach. Assume that one calculates the multimarket contacts of firm 1 in the left circle. In this approach to AVMMC, this paper assumes the distance bands of all firms to be independent markets. This means firm 1 appears in the three right circles in Figure 7 - 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, AVMMC2 is adopted. When calculating AVMMC2 for firm i

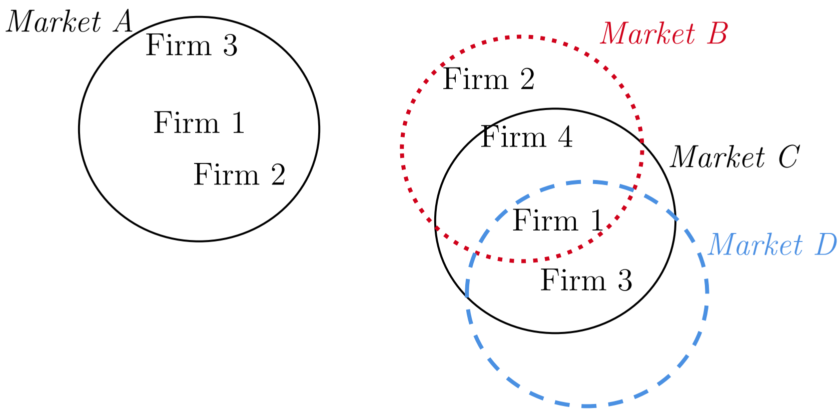


Figure 7: How to Calculate AVMMC

in market m, only markets where firm i is the focal firm are considered. Figure **??** explains this. Assume one is interested in the AVMMC2 of firm 1 in market A. Rather than considering two markets B and C in AVMMC, market C (firm 1's second focal market) is treated only as a 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).

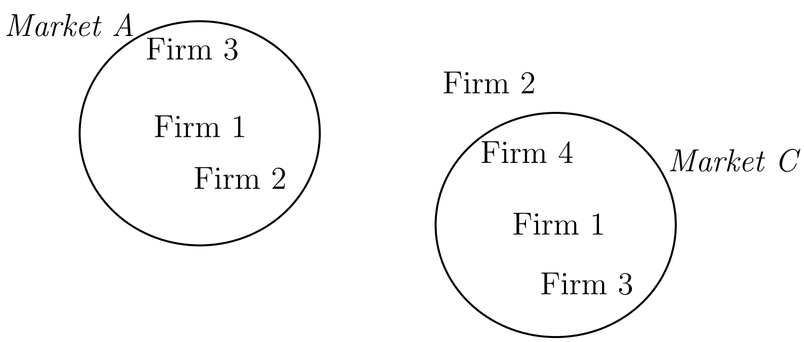


Figure 8: How to Calculate AVMMC2

Several assumptions are made in calculating AVMMC and AVMMC2. First, I assume that independent hotels are not included when calculating AVMMC and AVMMC2. Independent hotels are included when defining markets, especially in the Kth nearest neighbor approach as well as measuring market concentration. Second, I assume a hotel brand is considered to be a single firm, consistent with Fernandez and Marin (1998) and Silva (2015).

3.4 Descriptive Statistics

Table 3 shows the descriptive statistics of the variables used in this paper. The first panel shows the variables used, regardless of the market definition. The below panels (from the second to fifth panel) represents variables created under the distance metric (distance band Kth nearest neighbor approaches) and cluster approaches.

As mentioned earlier, the measures of MMC for independent hotels (non-branded hotels) are assigned as zero so there are many observations with zero. Likewise, these independent hotels are excluded in the estimation, while they are incorporated into the market concentration measure, HHI(Herfindahl Index) which is based on sales in the market.

Price is measured as the average daily rate. The number of room (No. of rooms) represents the capacity, and hotel rating (Rating) is measured by *TripAdvisor*. The number of hotels under the same brand and that under the same chain in the city are included as instruments. This will be discussed in detail in Section 4.

In the second panel, the descriptive statistics of the number of hotels in the distance band are reported. Within its distance band, a firm face competition with on average 20 hotels out of 470 hotels in Houston. The magnitude of AVMMC is greater than that of AVMMC2 since the first measure counts more markets than the second measure. Within a distance band, a hotel tend not to face the same brand hotel, while it is likely to face on average one hotel under the same hotel chain.

The measures of MMC in the third panel are AVMMC.KNN and AVMMC2.KNN. Compared to AVMMC and AVMMC2, these measures have smaller magnitudes since the Kth nearest neighbor approach only considers the four nearest hotels as rivals in a market.

The forth and fifth panels shows descriptive statistics of firms that are included in clusters created through DBSCAN. Since firms considered as noise points are excluded in this sample, the number of the total observations is smaller than all sample.

Figure 9 shows the distribution of MMC_{ij}. 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}.

4 Estimation and Model

4.1 Reduced Form Model

The reduced form model approach is used in this paper. Prices are a function of measures of multimarket contacts, product characteristics, and market structure:

$$P_j^{mt} = \alpha_1 MMC_j^{mt} + \beta X_j^{mt} + \epsilon_i^{mt} \tag{11}$$

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 and time fixed effects are included.

As prior studies (e.g., Ciliberto and Williams, 2014; Khwaja and Shim, 2017) indicate, there is more than one endogenous variable in reduced form models: prices

Table 3: Descriptive Statistics of Key Variables

Var.	N	Mean	St. Dev.	Min	Max
Price	1,880	85.849	52.001	118.453	400.75
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
Rating	1,880	1.763	1.659	3	6
No. of the same brand hotels	1,880	5.166	5.154	9	20
No. of the same chain hotels	1,880	18.226	18.375	34	55
Distance Band 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
No. of the same brand in market	1,880	0.07	0.294	0	3
No. of the same chain in market	1,880	0.853	1.412	1	7
Kth Nearest Neighbor Approach					
AVMMC.KNN	1,880	4.165	7.279	5	51
AVMMC2.KNN	1,880	0.917	1.725	1	12
No. of the same brand in market	1,880	0.011	0.105	0	1
No. of the same chain in market	1,880	0.183	0.387	0	1
Cluster Approach [1]					
Price	1,521	92.047	53.117	17.82	400.75
s_j	1,521	0.038	0.06	0.001	0.615
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
MMC_{jk}					
All hotels[2]	40,814	0.164	0.265	0.000	1.000
Branded hotels	14,696	0.456	0.250	0.091	1.000

1: Noise observations are dropped though DBSCAN.

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

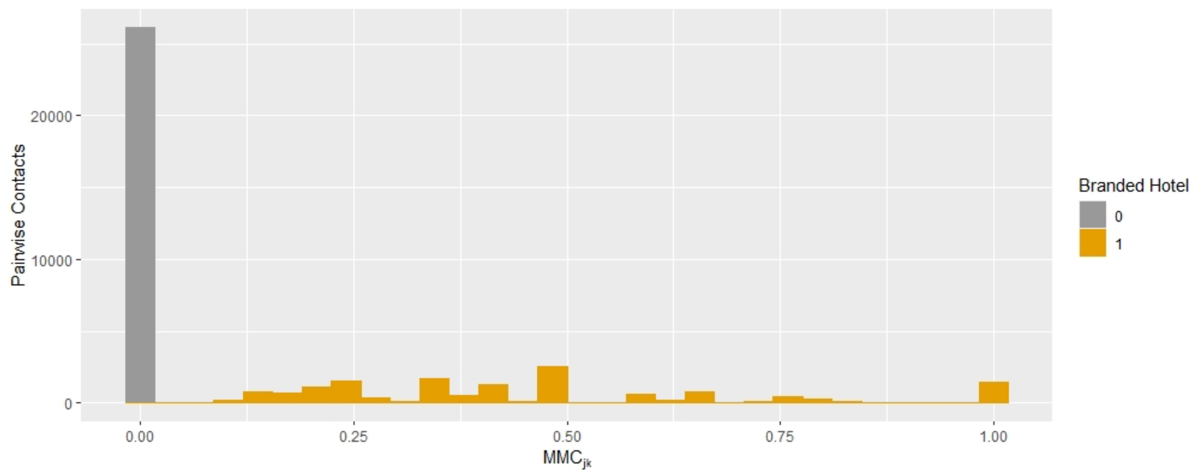


Figure 9: Distribution of MMC_{jk}

and multimarket contacts. Since reduced form models regress prices on the measures of MMC, the only endogenous variable of concern is MMC. This variable is highly affected by entry and exit decisions of the firms since the market structure in focal markets, as well as in other markets, determines multimarket contact. Thus, valid instruments should be correlated with entry and exit decisions. This paper uses two sets of variables affecting the entry and exit decisions: scale of the hotel (i.e., how many hotels are operated by a hotel brand) brand, and scope of the hotel chain with which the focal firm's brand is associated (i.e., how many hotel brands a hotel chain operates, how many hotel under different brands a hotel chain operates).

First, the scale of the hotel brand is valid in that its demand creation and cost-saving effects are correlated with entry and exit decisions. On the demand side, increases in scale create demand by increasing brand visibility in a market and discouraging entry of potential firms via spatial preemption (Schmalensee, 1978). In addition, on a large scale, hotel brands can lower input costs by negotiating with providers the input costs and sharing operational expenses, including advertising. Franchisors (hotel brands) are likely to add more units in a market when expecting benefits due to scale. Similar to Kosová et al. (2011), to measure the scale of a hotel brand, this paper uses the number of hotels under the same brand in a focal market and the number of hotels under the same brand within a city.

Second, the scope of a hotel chain also affects entry and exit decisions of individual brands and consequently influences the level of multimarket contact. 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 brand names associated with the 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 to these markets, hotel chains, as joint-profit maximizers, consider the potential effects of intra-chain competition (between their brands in the same chains) and inter-chain competition (between brands from different chains) (Kalnins, 2004; Wilson, 2011). Especially, the increased scope of hotel chains reduces competition between their brands, compared to the inter-chain competition (Wilson, 2011). In addition, as the scope of the hotel chain in a market increases, the scale of the hotel brand decreases. Thus, the scope of the hotel chain affects the entry/exit decisions of the focal hotel brand.

Furthermore, the scope of the hotel chain also affects 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.[5] Similar to cost saving due to the large scale of a hotel brand, hotel chains with large scope can reduce their costs by sharing supply networks and other costs, such as advertising and marketing. Hotel chains incur additional cost saving by training their franchisees, monitoring their units, or providing support to units from their chain headquarters. These provide cost saving due to the large scope affecting entry and exit decisions as well as the level of multimarket contacts. This paper uses the number of hotels within the same chain, excluding the focal brand to measure the effect of the scope of the hotel chain and those within a city.

4.2 Structural Model

4.2.1 Demand Side

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

$$\begin{aligned} u_{ij}^m &= \alpha p_j^m + X_j^m \beta + \xi_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij}^m \\ &= \delta_j^m + \zeta_{ig} + (1-\sigma)\epsilon_{ij}^m \end{aligned} \tag{12}$$

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:

[5]Some hotel brands, such as Courtyard by Marriott and Four Points by Sheraton, use the reputation of signature brands in the hotel chain.

$$s_j = s_{jg} \cdot s_g \tag{13}$$

$$s_{jg} = \frac{\exp(\frac{\delta_j}{1-\sigma})}{\sum_{j \in F_g} \exp(\frac{\delta_j}{1-\sigma})} = \exp(\frac{\delta_j}{1-\sigma})/D_g \tag{14}$$

$$s_g = \frac{D_g^{(1-\sigma)}}{\sum_{g'} D_{g'}^{(1-\sigma)}} \tag{15}$$

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

$$s_j = s_{jg} \cdot s_g = \frac{\exp(\frac{\delta_j}{1-\sigma})}{D_g^{\sigma}[\sum_{g'} D_{g'}^{(1-\sigma)}]} \tag{16}$$

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:

$$\ln(s_j) - \ln(s_0) = \alpha p_j + X_j \beta + \sigma \ln(s_{jg}) + \xi_j \tag{17}$$

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:

$$g(\theta^d) = E[Z_d \xi]. \tag{18}$$

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. Depending on the assumptions of these two aspects, there are 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.

The profit function in this paper includes two components of conduct parameters. 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:

$$\begin{aligned}\pi_f^m =& \underbrace{(p_j^m - mc_j^m)s_j^m M^m}_{\text{Own Profits}} \\ &+ \underbrace{\sum_{j' \in F_f} f_{vc}(I_{jj'}; \lambda_{vc})(p_{j'}^m - mc_{j'}^m)s_{j'}^m M_m}_{\text{Consideration of Vertical Control}} \\ &+ \underbrace{\sum_{k \neq j, j'} f_{mmc}(MMC_{jk}; \lambda_{mmc})(p_k^m - mc_k^m)s_k^m M_m}_{\text{Consideration of MMC}} \end{aligned} \tag{19}$$

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 19, this profit function for market m can be rewritten as

$$\Pi^m = \Lambda^m(P^m - MC^m)S^m M^m \tag{20}$$

All conduct parameters of interest in this paper are summarized in matrix Λ. Assume three hotels (hotels 1, 2, and 3; hotels 1 and 2 are under the same franchisor) in market m. The competition in market m is summarized as the following matrix

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

where $f_{vc}(I_{13}) = f_{vc}(I_{23}) = 0$ since hotel 3 is not a part of the franchisor with hotels 1 and 2.

The first order condition of the profit function (Equation 19) is as follows

$$\begin{aligned} & s_j^m + (p_j^m - mc_j^m)\frac{\partial s_j^m}{\partial p_j^m} \\ & \quad + \sum_{j'} (p_{j'}^m - mc_{j'}^m)\frac{\partial s_{j'}^m}{\partial p_j^m} f_{vc}(I_{jj' \in F_f}) \\ & \quad + \sum_{k} (p_k^m - mc_k^m)\frac{\partial s_k^m}{\partial p_j^m} f_{mmc}(MMC_{jk}) = 0 \end{aligned} \quad (22)$$

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

Given consumer preferences and the specification of the supply side, marginal costs are defined as

$$mc_j^m(\lambda_{vc}, \lambda_{mmc}) = p_j^m - \Omega^{-1}(\lambda_{vc}, \lambda_{mmc}) \cdot s_j^m(\hat{\alpha}, \hat{\beta}) \quad (23)$$

where $\Omega = -\Lambda \cdot \partial s/\partial p$ ($\partial s/\partial p$ is a matrix form of $\frac{\partial s_k^m}{\partial p_j^m}$).

This paper specifies the marginal costs for product j in market m as

$$mc_j^m = W_j^m \rho + \omega_j^m \quad (24)$$

where W_j^m is a set of cost factor of product j in market m and ω_j^m is the unobserved marginal costs.

This paper use the following models for the conduct parameters in Equation 19

$$f_{vc}(I_{jj'};\lambda_v) = \frac{exp(\lambda_v)}{1 + exp(\lambda_v)} I_{jj'} \quad (25)$$

$$f_{mmc}(MMC_{jk};\lambda_{mmc}) = \frac{exp(\lambda_{mmc})}{1 + exp(\lambda_{mmc})} MMC_{jk}. \quad (26)$$

where $I_{jj'}$ equals one if hotel j and j' are under the same franchisor; otherwise $I_{jj'}$ is zero. $MMC_{jk} \in [0, 1]$ represents the pair-specific multimarket contacts between j and k. Given those specifications, the estimated conduct parameters are between 0 and $1 (0 \leq f_{vc} \leq 1, 0 \leq f_{mmc} \leq 1)$.

Using Equations 23 and 24, the unobserved marginal costs is rewritten

$$\omega_j^m = p_j^m - W_j^m \rho - \Omega^{-1}(\lambda_{vc}, \lambda_{mmc}) \cdot \hat{s}(\hat{\alpha}, \hat{\beta}) \quad (27)$$

With the instruments for the supply side, Z_s, the moment conditions are defined as

$$g(\theta_s) = E(Z_s\omega) = 0 \tag{28}$$

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

Given the moment conditions of Equation 28, GMM estimation is used to estimate for θ_s. The instruments used are the numbers of the same branded hotels in the market(city) and the number of hotels under the same hotel chain in the market(city). These instruments are valid since marginal costs of branded hotels are affected by the presence of the same branded hotels or hotels under the same hotel chains. Franchisors, or hotel chains (franchisors with multiple hotel brands), achieve economies of scale when their hotels are closely agglomerated within geographic areas or a city.

For the supply side, this paper estimates several models with different specifications of vertical control and MMC (Model 1 to 3): 1) No Vertical Control and No MMC, 2) Full Vertical Control and MMC, and 3) Partial Vertical Control and MMC. Each model can be presented with the prior hypothesized example of a market with three hotels (hotels 1 and 2 under the same firm(franchisor)). Matrix Λ for each model is presented as follows:

$$\Lambda^1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\Lambda^2 = \begin{bmatrix} 1 & 1 & f_{mmc}(MMC_{13}; \lambda_{mmc}) \\ 1 & 1 & f_{mmc}(MMC_{23}; \lambda_{mmc}) \\ f_{mmc}(MMC_{31}; \lambda_{mmc}) & f_{mmc}(MMC_{32}; \lambda_{mmc}) & 1 \end{bmatrix}$$

$$\Lambda^3 = \begin{bmatrix} 1 & f_v(I_{12}; \lambda_{vc}) & f_{mmc}(MMC_{13}; \lambda_{mmc}) \\ f_v(I_{21}; \lambda_{vc}) & 1 & f_{mmc}(MMC_{23}; \lambda_{mmc}) \\ f_{mmc}(MMC_{31}; \lambda_{mmc}) & f_{mmc}(MMC_{32}; \lambda_{mmc}) & 1 \end{bmatrix}$$

where Λ represents the ownership structure of each specification.

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

5 Results

5.1 Results of Reduced Form Models

Tables 4 summarizes the estimation results of the instrument variable models with two different market definitions and two different measures of MMC. The results from both tables support the view that hotels with more multimarket contacts tend to charge higher prices. This means that multimarket contacts facilitate collusive behaviors, consistent with prior studies using the hotel industry as a sample (Fernandez and Marin, 1998; Silva, 2015).

Table 4: Estimation Under Distance Metric Approach

	Dependent variable:			
	Price			
	(1)	(2)	(3)	(4)
AVMMC	0.239***			
	(0.037)			
AVMMC2		5.197***		
		(0.777)		
AVMMC.KNN			1.179***	
			(0.200)	
AVMMC2.KNN				4.993***
				(0.838)
Rating	25.954***	26.174***	28.543***	28.467***
	(0.677)	(0.666)	(0.762)	(0.758)
No. of Room	0.011	0.012	0.008	0.007
	(0.007)	(0.007)	(0.008)	(0.008)
HHI	−27.286***	−31.358*** −10.881	−13.214	
	(6.215)	(6.192)	(10.869)	(10.958)
Downtown	48.975***	47.959***	46.731***	47.051***
	(3.421)	(3.367)	(3.627)	(3.641)
Airport	−13.458***	−12.631***	−10.112**	−9.988**
	(3.737)	(3.709)	(4.014)	(4.026)
Constant	21.120***	21.212*** 16.750***	18.175***	
	(2.707)	(2.654)	(4.121)	(4.027)
Fixed Effect				
Quarter	Yes	Yes	Yes	Yes
Observations	1,274	1,274	1,274	1,274
R^2	0.714	0.717	0.668	0.666
Adjusted R^2	0.712	0.715	0.665	0.664
Note:				*p<0.1; **p<0.05; ***p<0.01

Depending on the market definition, or the measures of MMC, the economic relevance of the effects of MMC varies. Thus, I use the standard deviation of the measures of MMC to interpret the meaning of the coefficients of MMC. In Table 4, one standard deviation increase in AVMMC raises prices by $\$6.998 = 0.239 \times 29.279$. Similarly, one standard deviation increase in AVMMC2 makes prices higher by $\$6.932 =$

5.197 $*$ 1.334. Both cases show similar increased prices due to one standard deviation increases in the measures of MMC.

From Table 4, as AVMMC.KNN increases by its one standard deviation, prices rise by \$8.582 $= 1.179 \times 7.279$. Similar results are found with AVMMC2.KNN: prices increase by \$8.613 $= 4.993 \times 1.725$ due to one standard deviation increase in AVMMC2.KNN.

The reason that prices with the Kth nearest neighbor approach increase slightly greater than with distance band approach is that a firm can be more sensitive to small sets of its closest rivals.

5.2 Results of Structural Model

Demand Side Estimates of the demand side are summarized in Table 5. All signs of the coefficients in the demand side are expected. Consumers dislike paying high price 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 increase. 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.

Table 5: Results of Demand Estimation

	Dependent Variable:
	log(sj) - log(s0)
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)
log(sjg)	0.441^{***}
	(0.092)
Constant	2.055^{***}
	(0.355)
Fixed Effect: Quarter	Yes
GMM Objective Values	0.1416
Note:	*p<0.1; **p<0.05; ***p<0.01

Estimates of the demand side are used in estimating the supply side and follow-up counterfactual analysis.

Supply Side Table 6 summarizes the estimates of the supply side with three different specifications (Model 1 to Model 3). The following explanations are consistent across these models. On the cost side, this paper finds that the marginal cost of 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 columns 2 and 3 in Table 6 support the view that firms facilitate collusion in prices through multimakret contact. 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 6: 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 7 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 7: Estimated Conduct Parameters

	Model 1	Model 2	Model 3
MMC ($\hat{f}_{mmc}$)	0	0.5499***	0.9588***
Vertical Control ($\hat{f}_{vc}$)	0	1	0.1711**
Note:	*p<0.1; **p<0.05; ***p<0.01		

5.3 Counterfactual Analysis

To measure how collusive behaviors via MMC affect consumer welfare, this paper conducts a counterfactual analysis. The counterfactual scenario is that a government regulation prohibits collusion resulting from MMC, and firms consequently set their prices competitively. Table 8 summarizes how conduct parameters are set up under the counterfactual scenario.

Table 8: 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	0.1711

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

$$p^* = mc + \Omega^{-1}(p^*)s(\hat{\alpha}, \hat{\beta}, p^*) \tag{29}$$

where the first component in the right hand side, mc is estimated under the original condition (the pre scenario).

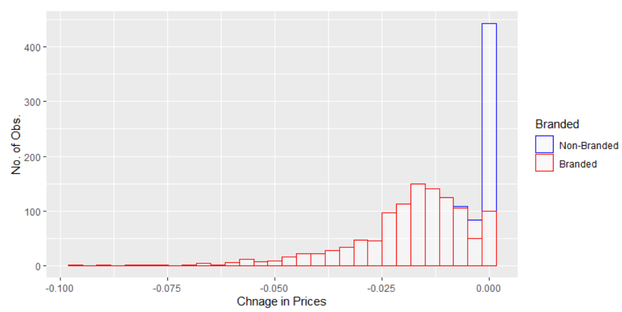
The results of counterfactual analysis are summarized in Table 9. On average, with regulations against collusion via MMC, prices would drop by approximately 1.4 or 1.54%. While there is little change in prices for non-branded hotels for which this paper assumes no multimarket contacts, the average prices 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).

Table 9: Comparison of Average Observed Prices and Equilibrium Prices

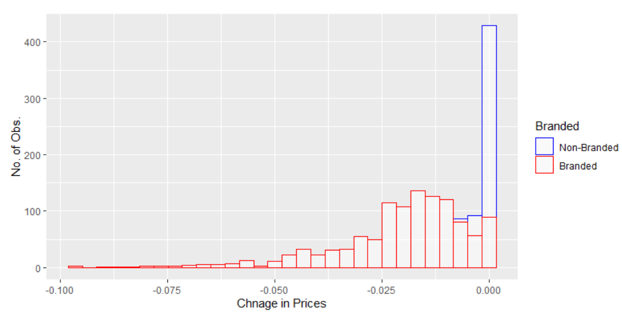
	Observed	Model 2		Model 3	
	p	p^*	% Change	p^*	% Change
Non-Branded	61.79	61.76	0.00%	61.76	0.00%
Branded	102.12	100.59	-1.60%	100.46	-2.00%
All	92.05	90.89	-1.40%	90.79	-1.54%

p: the observed average price
$p*$: the estimated average price

Figure 10 shows the distribution of price change under the counterfactual analysis. As mentioned earlier, most price changes under the post scenario happen for branded hotels. In addition, most observations are between 0% and 2%.



(a) Changes in Price Under Model 2



(b) Change in Prices Under Model 3

Figure 10: Price Changes in the Counterfactual Analysis

6 Conclusion

This paper examines how multimarket contact facilitates price collision using a sample of hotels in Houston, TX. The results of this paper confirm collusive behaviors through multimarket contact in the hotel industry. The contribution of this paper is twofold. First, this paper provides two empirical approaches to define markets within a metropolitan area: the distance metric approach by Pinkse et al. (2002) and density-based spatial clustering with noises (DBSCAN), a clustering algorithm. As results, this paper uses the 2.5 miles distance band and the four nearest neighbors defined by the distance metric approach. Twenty-one markets are defined under DBSCAN. Estimations of analyzing the effect of MMC on price are consistent through the different market definition.

Second, using the structural models, this paper takes into account the effect of vertical control by upstream firms over downstream firms when estimating the effect of MMC. These two effects are simultaneously estimated without any prior assumptions of vertical control. The results indicate that with strict assumptions about vertical control, the effect of MMC is underestimated, even though with or without this assumption, a positive relationship between MMC and price is empirically confirmed.

This paper further investigates the impact of multimakret contact on consumer welfare. Counterfactual analysis shows that regulation of collusive behavior via MMC leads to decreases in prices (around 1.5%), mostly of branded hotels. This result suggests that when estimating the impact of mergers that may change the levels of MMC, 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 branded portfolio of a hotel chain. It would be interesting if the existence of multi-branded chains were 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 discourse documents of the sample hotel brands in this study are retrieved from the franchise e-filing database of the state of Wisconsin.

This study finds three evidences in the FDDs allowing 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 by 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 condition and inventories/demand of individual hotels.[6] 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 inform them of their suggested prices. Table 10 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 and chains. Table 10 shows the revenue management services most franchisors provide in the sample. For example, Red Lion Hotels' *Revenue Management Insight* provides the market reports covering regional competitors and their pricing. Wyndham has different levels of the consulting services (Platinum, Gold and Diamond) with a mandatory service for opening hotels. These services are mostly optional for franchisees, but with some exceptions. Most hotel brands require that franchisees 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.[7]

The second evidence that franchisors influence franchisees' pricing policies is national group sales promotions. Most franchisees have options to participate in national

[6] 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 academics.

[7] Most hotel chains have uniform policies for revenue management consulting services across their brands, except Hyatt. Hyatt indicates that their 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.

or group sales given that prices and quantities are 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 this degree of cooperation between franchisees, or between franchisors and franchisees, franchised units under these cooperative arrangements tend to work as single entities.

In addition to these three types of evidence found in their FDDs, hotel 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 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 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 10: 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 10)		
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 Robust Check of Reduced Model Analysis

B.1 Estimation of Reduced Model Under DBSCAN

This paper conducts additional estimates of reduced form models under markets defined by DBSCAN. The results of the reduced form estimation are summarized in Table 12. These estimates are consistent with those with other market definitions, but the coefficient of AVMMC.CL, the key variable of measuring the average level of MMC, becomes insignificant in the IV model (Column (2) in Table 12). This is largely because each market has more firms. Thus, different estimation strategies, such as utilizing pair specific measures of MMC are necessary rather than average measures of MMC.

Table 11: Descriptive Statistics under DBSCAN

	N	Mean	St. Dev.	Min	Max
AVMMC.CL	1,521	0.616	0.736	0	4
No. of the Same Brand Hotels in Market	1,521	1.055	1.160	0	5
No. of the Same Chain Hotels in Market	1,521	2.555	3.482	0	16

Table 12: Estimation under the DBSCAN approach

	Dependent variable:	
	Price	
	OLS	*IV*
	(1)	(2)
AVMMC.CL	7.789***	0.742
	(1.119)	(14.832)
Rating	26.852***	26.925***
	(0.699)	(0.727)
No. of Room	-0.001	-0.005
	(0.007)	(0.012)
HHI	−37.201**	−38.331**
	(15.929)	(16.377)
Downtown	48.535***	47.891***
	(3.554)	(3.860)
Airport	−10.222***	−11.055***
	(3.758)	(4.204)
Constant	21.341***	29.046*
	(2.655)	(16.392)
Fixed Effects: Quarter	Yes	Yes
Observations	1,148	1,148
R^2	0.717	0.707
Adjusted R^2	0.715	0.705
Note:	*p<0.1; **p<0.05; ***p<0.01	

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