

# Multimarket Contact in the Hotel Industry

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## Abstract

Since Bernheim and Whinston (1990), growing number of studies have empirically examined if multimarket contact facilitates collusion in various industries (e.g., airlines, cement, movie theaters). This paper contributes this literature by investigating the effect of multimarket contacts on prices in the hotel industry in which firms tend to closely locate in the markets, such as metropolitan areas. To date, insufficient attention has been paid to such geographic areas, even though firms face competition of similar sets of rivals in different markets, even in an MSA. Based on the notion that rivals exert strong influence on firms' prices, this paper empirically defines markets in a metropolitan hotel market by using the distance metric approach by Pinkse et al. (2002). As a result, two valid market definitions are formed: rivals with 2.5 miles radius, and the fifth nearest neighbors from each hotel. With these definitions, markets are empirically formed and reduced form model analysis is conducted to evaluate the effects of multimarket contact on price. The results support that hotels with more multimarket contacts of their rivals charge higher prices under both the market definitions.

## 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 markets or regions. This inter-firm recognition across markets can create circumstances in which competition between firms is reduced if behavior in different markets is 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 sustain cooperation. Since Bernheim and Whinston (1990), many empirical studies have examined the effect of multimarket contacts on collusive pricing in various industries: airlines (e.g., Evans and Kessides, 1994; Gimeno and Jeong, 2001; Ciliberto and Williams, 2014), cement (Jans and Rosenbaum, 1997), movie (e.g., Feinberg, 2014), lumber (Khwaja and Shim, 2017) and hotel (e.g., Fernandez and Marin, 1998; Silva, 2015).

This paper contributes to this literature by analyzing markets that have been ignored in empirical literature in this field: metropolitan statistical areas (MSAs) in which firms in retail or service industries have multiple units/stores. Consumer demand is likely to be concentrated in small geographic areas within MSAs, creating conditions where firms face similar sets of rivals in different regions that are even within the same MSA (Kalnins, 2006; Chung and Kalnins, 2001). In addition, through vertical contracts, such as franchising, in retail and service industries, firms as franchisors can add more franchised units without significant capital investments. Thus, MSAs present the opportunity to test the effect of MMC within defined geographic boundaries. However, one might argue that franchisors are not able to control the pricing policies of their franchisees. 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, Kosova 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 have some levels of control over pricing policies of their franchisees.

One additional step is needed to analyze the effect of MMC on prices in MSAs: identifying well-defined markets in MSAs. This paper uses two approaches to define markets: distance band and  $k$ th nearest neighbor approach.<sup>1</sup> The first one define a market as a set of rivals within a given radius from a focal unit, while the later considers a market as rivals within the  $k$ th nearest one. Both approaches require predetermined parameters to define markets: radius and the number of rivals ( $k$ ). Unlike prior studies which relied on predetermined values for these parameters, this paper estimates these parameters by using the distance metric approach proposed by Pinkse et al. (2002). This distance metric approach calculates empirically valid values for these parameters. Given these estimates, markets within a MSA will be appropriately defined.

This paper investigates the effect of MMC on collusive pricing by analyzing hotels in Houston, Texas. The Houston hotel market provides an ideal condition to test the effect of MMC since most hotels are associated with hotel chains. Each hotel brand (franchisor) has multiple units in more than one geographic area in Houston. Within this city, hotel brands, or hotel chains, also easily monitor prices of their units as well as those of their rivals, allowing the hotel brands to coordinate within the city, similar to the argument in Khwaja and Shim (2017).

The paper uses the reduced form model to estimate the effect of MMC on prices, similar to prior studies (Evans and Kessides, 1994; Fernandez and Marin, 1998; Silva, 2015). The instrument variable approach is used to deal with the endogeneity of MMC. For instruments, variables affecting entry/exit decisions are used, such as the number of hotels under the same brands and the number of other branded hotels under the same chain since contacts between firms in focal markets and other markets are determined by firms' entry/exit decisions. Even though structural modeling has some advantages since most studies using this approach use pair-wise multimarket contacts (Ciliberto and Williams, 2014; Khwaja and Shim, 2017), this approach is less feasible for this paper since the structural approach requires clear market definitions, including shares of each product and outside options in a market. The two market definitions used in this paper cannot create non-overlapped markets. Thus, only reduced form models are used.<sup>2</sup>

Using 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). Five neighbors are also determined as influential rivals. This is consistent with a survey of hotel managers conducted by Kalnins (2006). By incorporating these estimates and constructing markets, this paper estimates the effect of MMC on prices. A positive correlation between price and the measures of MMC is confirmed, indicating that firms with more contacts with rivals in other local markets within a MSA charge higher prices. Additional robust checks are conducted with different measures of MMC, and the similar results are obtained.

This paper is organized as follows. Section 2 summarizes a theoretical model of MMC and related empirical literature. Section 3 presents data sets, empirical models of market definition, and the measures of MMC. Section 4 shows the reduced form model and its estimation. Section 5 concludes this paper.

## 2 Literature Review

In this section, I describe the theoretical intuition of Bernheim and Whinston (1990) and then summarize empirical studies about MMC.

<sup>1</sup>I used density based clustering analysis with noise(DBSCAN), one of the clustering methods, to define market. Market clustering and estimation of the IV models are included in the appendix.

<sup>2</sup>Using the cluster analysis models, I will define markets without overlapping later. With these markets, structural models are feasible.

Bernheim and Whinston(1999, hereafter BM) propose a theoretical model in which multimarket contact makes collusion more feasible in the repeated game setting. In the repeated game, there are  $n$  firms (firm  $i = 1, \dots, n$ ) in market  $k = 1, \dots, K$ . The profit function of firm  $i$  is  $\pi_{ik} = \pi_{ik}(p_{ik}, p_{jk})$ . If there is only one market ( $K = 1$ ), firm  $i$  faces the following incentive compatibility constraint in which a firm chooses to cooperate:

$$\pi_{ik}(R_i(p_{jk}), p_{jk}) + \frac{\delta}{1 - \delta} v_{ik} \leq \frac{1}{1 - \delta} \pi_{ik}(p_{ik}, p_{jk}), \forall i \neq j \quad (1)$$

where  $R_i()$  is the best response of  $p_{jk}$ ,  $v_{ik}$  is the payoff under optimal punishment, and  $\delta$  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 ( $k > 1$ ), BM argue pooling incentive compatibility constraints of each market creates interdependency of firms across markets. This means a firm chooses its price in a market by considering rivals in this market, as well as other markets. The pooling incentive compatibility constraint is as follows:

$$\sum_k (\pi_{ik}(R_i(p_{jk}), p_{jk}) + \frac{\delta}{1 - \delta} v_{ik}) \leq \sum_k (\frac{1}{1 - \delta} \pi_{ik}(p_{ik}, p_{jk})) \quad (2)$$

BM argue that this pooling incentive compatibility constraint does not guarantee cooperation. The pooling constraint would be the same as the constraint in the single market case if markets are homogeneous. However, if markets are heterogeneous, or if firms provide differentiated products across markets, the pooling constraint would be satisfied. This means MMC facilitates collusive behavior.

Since BM's groundbreaking theoretical framework of MMC, a number of empirical studies examine the effect of MMC on collusive behavior, especially the relation between MMC and prices in various industries. Even though there is some discrepancy in the results, most empirical studies find supporting evidence for BM's framework that MMC facilitates collusive pricing.

In this literature on MMC, empirical studies can be categorized in terms of the estimation methods used: the reduced form models (Evans and Kessides, 1994; Gimeno and Woo, 1996; Fernandez and Marin, 1998; Waldfogel and Wulf, 2006; Silva, 2015; Bilotkach, 2011) and the structural models (Ciliberto and Williams, 2014; Khwaja and Shim, 2017; Molnar et al., 2013). Most studies fall in the first category. The reduced form models calculate the average of multimarket contacts for each firm, rather than the firm-pair specific measures of MMC. Evans and Kessides (1994) presents one of the first studies in this categories and 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 MMC on 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) analyze the effect of MMC on non price product characteristics (the frequency of services), in the airline industry. Using the merger between US Airways and American West Airlines as a demand shock that change levels of MMC significantly, Bilotkach finds that the frequency of services is lowered in markets with higher levels of MMC after the merger.

The second group of studies adopt the structural framework of Berry et al. (1995). Molnar et al. (2013) examine the effect of MMC in the Italy retail banking industry, especially the deposit side. With several conduct parameters aiming to capture the characteristics of market structure, they find that banks with high levels of MMC act less competitively than ones with lower MMC. Similarly, Ciliberto and Williams (2014) adopt similar approach of conduct parameters in the supply

side of their structural model using the airline industry as a sample. The authors incorporate the firm-pair specific measures of MMC into the conduct parameters, allowing firms to consider rivals differently depending on the levels of MMC. The results confirm that airlines presenting in similar markets sustain collusive equilibrium. Khwaja and Shim (2017) extend the approach of Ciliberto and Williams (2014) by using a random coefficient model for demand estimation.

Since this paper analyzes inter-market competition, a clear market definition plays a crucial role in identifying local competition and calculating levels of MMC (Evans and Kessides, 1994). Depending on the industry, some studies contain clear market definition, while others rely on third party market definitions. Studies of the airline industry use city-pair routes as a market definition (Evans and Kessides, 1994; Gimeno and Woo, 1996; Ciliberto and Williams, 2014), while studies of the Spanish hotel industry use government defined districts based on tourism and business activities to define markets (Fernandez and Marin, 1998; Silva, 2015). However, such market definitions would underestimate measures of MMC since the markets are defined to be relatively large.<sup>3</sup> Rather than relying on the third party market definitions, this paper uses an empirical approach to define markets for each hotel. Section 3 will discuss this empirical approach to define markets in MSAs.

To test whether multi-market contact facilitates collusion in MSAs in the hotel industry, it is necessary that franchisors have influence on pricing at franchised units, or stores within a geographic area. In other words, hotels under the same brand could operate as a single entity or be governed by only a few personals at least in pricing. Given this condition, franchisors face competition with other franchisors in multiple geographic markets, giving the franchisors both capacities and incentives to enter into price collusion with other franchisors. Without these conditions, markets would consist of single-unit owners that would rarely face similar sets of competitors in multiple markets. Thus, it is crucial that this study verify this necessary condition exists. First, to identify any clauses to allow franchisors to affect franchisees' pricing policies at their units in franchise contracts, this paper analyzes franchise discourse documents (FDDs), a legal document presenting a franchise contract for potential franchisees (buyers).

Franchise discourse documents of the sample hotel brands in this study are retrieved from the franchise e-filing database of the state of Wisconsin.<sup>4</sup>

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 the 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.<sup>5</sup> 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 1 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 1 shows

<sup>3</sup>Fernandez and Marin (1998) mentions this market definition; 83 markets are identified. Example 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.

<sup>4</sup>Even though the sample of this study is hotels in Houston, TX, using the 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 to file FDDs. Franchisors are only asked to file the exception form under the *Texas Business Opportunity Act*

<sup>5</sup>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.

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 there are some exceptions. Most hotel brands require that franchisees use the 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.<sup>6</sup>

The second evidence that franchisors influence franchisees' pricing policies is national group sales promotions. Most franchisees have options to participate in national or group sales given prices and quantities 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 these cooperation between franchisees, or between franchisors and franchisees, franchised units under these cooperatives tend to work as single entities.

In addition to these three evidences 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 controls, 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 the antitrust law, hotel franchisors do not have direct controls on pricing of franchisees. Instead, franchisors use revenue management system 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.

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<sup>6</sup>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 their revenue management services.

Table 1: 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	iDeas(Required; a third-party(SAS) revenue management system), ChoiceRM Revenue Management Program(Optional)
	Comfort	
	Main Stay	
	Sleep Inn	
	Suburban	
	EconoLodge	
	Rode Way Inn	
ESA	Extended Stay	iDeas (Required)
G6	Motel 6	G6ROW Rate Administration(Required), G6ROW Revenue Optimization(Optional)
	Studio 6	
Hilton	Doubletree	QnQ (Required), Revenue Management Consolidated Center(Optional, but required for some cases)
	Embassy	
	Hampton	
	Hilton Garden	
	Hilton	
	Home 2	
Hyatt	Homewood	Hyatt central system (Required), Revenue Optimization Service(Option, but required for Hyatt Regency)
	Hyatt House	
	Hyatt Place	
	Hyatt Regency	
IHG	Candelwood	IHG Concerto(Required), Yield & Price Optimization(Required), Revenue Mangement for Hire Service(Optional, but required for some cases)
	Holiday Inn	
	Indigo	
	InterContentient	
	Staybridge	
	Crowne Plaza	
La Quinta	La Quinta	Revenue Management Services
Marriott	Aloft	Revenue Management Advisory Services, Cluster Revenue Management (Both optional, but required for some cases)
	Courtyard	
	Element	
	Le Merrian	
	Marriot	
	Sheraton	
	Springhill	
	Westin	
	Fairfield	
	Four Points	
Raddison	Country Inn	Revenue Optimization Program (Optional)
	Park Inn	
	Raddison	
Red Lion	Best Value Inn	IDeas G3(Required), Revenue Management Insight (Optional)
	Guest House	
	Knights Inn	

<i>Continued from the previous page</i> (Table 1)		
Chain	Brand	Name & Optional(Required)
Wyndham	Day Inn	
	Hawthorn	
	Howard	
	Microtel	
	Ramada	Central Rate and Inventory Support
	Super 8	Program(Required), Short Term Revenue
	Travelodge	Management Services(RMS) (Required), Platinum,
	Wingate	Gold, and Diamond RMS (Optional)
	Wyndham Garden	
	Wyndham	
	Baymont	

### 3 Data

#### 3.1 Data Source

The source of data for this paper is hotels in Houston, Texas from the first quarter 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*.

#### 3.2 Distance Metric Approach

This paper use the distance metric approach to estimate the parameters (distance limit and the  $k$ th nearest neighbor) used to define markets.

##### 3.2.1 Estimation for Distance Limit

Using the framework of (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  $i$  faces the indirect demand function:

$$q_i = a_i + \sum_j b_{ij}p_j + \epsilon_i, i, j = 1, \dots, n \quad (3)$$

where  $a_i$  is demand or cost characteristics of firm  $i$ .  $b_{ij}$  is the price effect on  $q_i$  ( $b_{ii}$  for own-price,  $b_{ij}$  for cross-price effects).

The profit function is  $\pi_i = p_i q_i = p_i(a_i + \sum_j b_{ij}p_j)$ . 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 parameter to be estimated, Pinkse et al. (2002) treat  $b_{ij}$  as a function of distance between  $i$  and  $j$  ( $b_{ij} = g(d_{ij})$ ). Assume that the price coefficient,  $b_{ij}$  is a function of the distance between firm  $i$  and  $j$ ,  $b_{ij} = g(d_{ij})$ . From the first order condition and the assumption on  $b$ , the price reaction function is as follows:

$$p_i = R(p_{-i}) = \sum_k \beta_k x_j^k + g(d_{ij})p_j + \epsilon_i \quad (4)$$

where  $x^k$  is one of the product characteristics of firm  $i$  and  $\epsilon_i$  is a random shock.

This can be rewritten in a matrix form:

$$P = R(P') = X\beta + GP' + \epsilon \quad (5)$$

$G = g(d_{ij})$  and  $P'$  is a cross price matrix with zero diagonal elements.

Assume  $G = \gamma W$ .  $\gamma$  is the only parameter estimated and  $W$  is a matrix that captures a firm-pair difference in product characteristics. Thus, the price reaction is as follows:

$$P = X\beta + \gamma WP + \epsilon, \quad (6)$$

where

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

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

$$b_{ij} = \hat{\gamma} \frac{1}{d_{ij}} \quad (8)$$

As the distance increases,  $b_{ij}$  approaches zero, indicating that rivals ( $j \neq i$ ) distant from firm  $i$  have little effect on firm  $i$ 's price.

For this estimation of the price reaction function, this paper uses the fixed-effects model. The result is summarized in the following table. The estimates for  $\gamma$  is 0.0016 and with the median number of firms (95.624 firms), the cross-price coefficient is 1.530.

Table 2: Price Reaction Function Estimation

<i>Dep. Var.: ADR</i>		
Var.	Coeff.	C.I (95%)
WP ( $\gamma$ )	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	Location, Time	
Observations	13,868	
R <sup>2</sup> (Adj. R <sup>2</sup> )	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.

### 3.3 Estimation of $k$ th neighborhood

Using the distance metric approach by Pinkse et al. (2002), this papers also estimates the  $k$ th 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 of number of the closest rivals. For example, if there are three closest rivals to be tested,  $W$  is



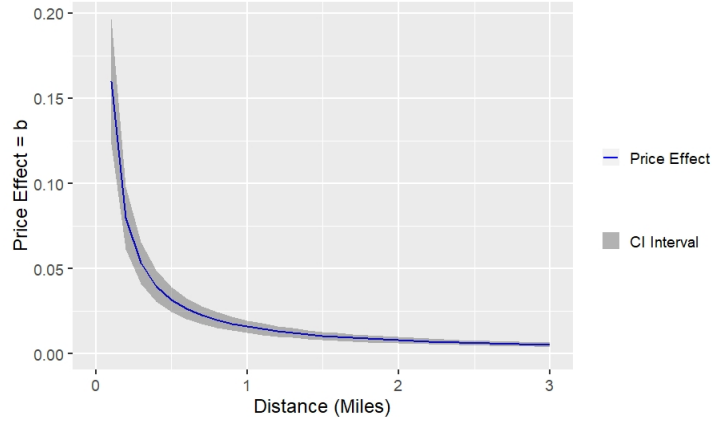


Figure 1: Price Effects (Changes in Distance)

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

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 remain constant, indicating adding additional competitions does not change the level of competition.

Figure 2 shows changes in  $\gamma$ , 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 in  $W$  beyond four or five rivals added in  $W$ . This paper conservatively uses four as the number of valid neighbors ( $k = 4$ ). This is consistent with prior studies (Kalnins, 2006).

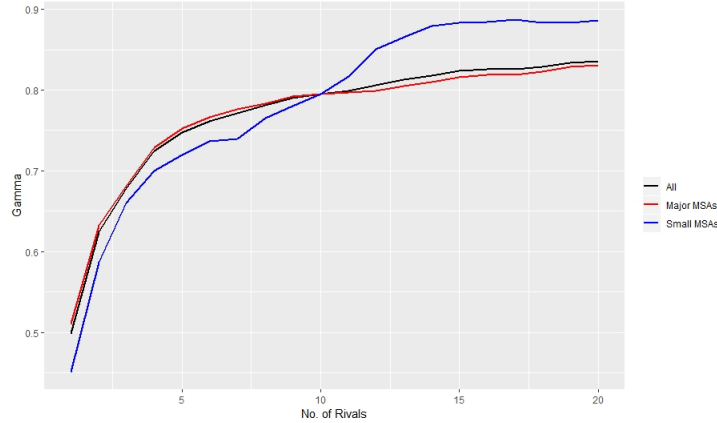


Figure 2: Changes in Price Coefficients with the Number of Neighbors

### 3.4 Issue of Market Definition

Using the 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. In the distance band approach, assume 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 explains this issue.

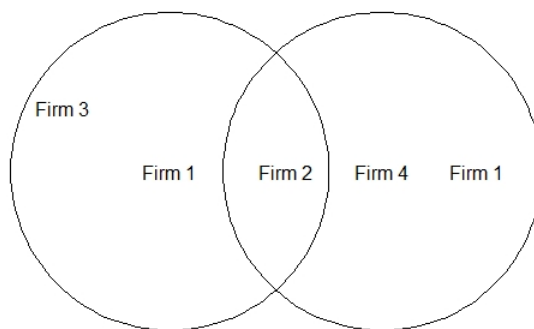


Figure 3: Double Counting

In Figure 3, the left circle represents the market of firm 1; the right circle, the market for firm 4. Texts in the figure represents 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, 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 the focal distance band.

For the  $k$ th nearest neighbor approach, I exclude the closest hotels near rivals for a hotel. The procedure is as follows: once firm  $i$  is chosen to create a market, its 4 nearest neighbors are selected based on the pair-wise distance (the first degree neighbors for firm  $i$ ). Each of the first neighbors has its 4 nearest neighbors (the second degree neighbors for firm  $i$ ). The third degree neighbors for firm  $i$  is formed as the 4 nearest neighbors of the second degree neighbors. I exclude the second and third degree neighbors when calculating the level of MMC of firm  $i$ . By doing this, I can circumvent both double counting and indirect effect issues.

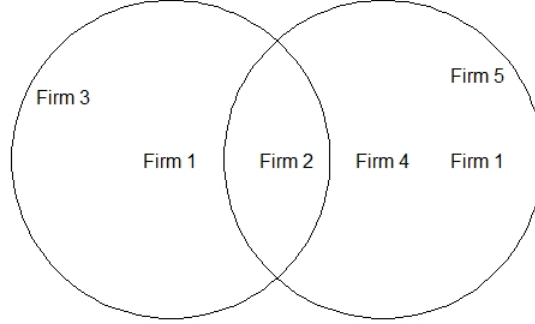


Figure 4: Indirect Effects

### 3.5 Measure of Multimarket Contacts

Since this paper uses only reduced form models, the measures of MMC should be the average of MMC across rivals in the market, similar to Silva (2015); Gimeno and Woo (1996); Evans and Kessides (1994). The average multimarket contact of firm  $i$  in market  $m = 1, \dots, M$  with rival  $j = 1, \dots, J_m, j \neq i$  is:

$$AVMMC_{im} = \frac{\sum_{j \neq i} I_{im} \cdot I_{jm} \sum_{n \neq m} I_{in} \cdot I_{jn}}{N_m - 1}$$

where  $I_{im}$  is equal to 1 if firm  $i$  is in market  $m$ . Otherwise, it is zero.  $N_m$  is the total number of firms in market  $m$ . A set of markets is all distance bands (or all markets created by the  $k$ th nearest neighbor approach) in which firm  $i$  presents.

The market definition used in this study does not create an exclusive market for a firm. This means a firm might appear multiple time, 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. The method of calculating the level of MMC is the same in both measures, while they are different in recognizing other markets given a focal market.

**AVMMC** considers all possible markets created by the distance band or the  $k$ th nearest neighbors approach if the firms are sufficiently far away from a focal firm. Figure 5 shows how to calculate AVMMC graphically. In this figure, markets are created by the distance band approach, but this logic may apply for the  $k$ th nearest neighbor approach. Assume that one calculates the multimarket contacts of firm 1 in the left circle. In this approach to AVMMC, I assume the distance bands of all hotels as independent markets. This means firm 1 appears in three right circles (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 is  $3/2 = 1.5$  (total number of contacts of rivals in other markets (B,C, and D) / No. of rivals in the focal market (A), AVMMC=1.5).

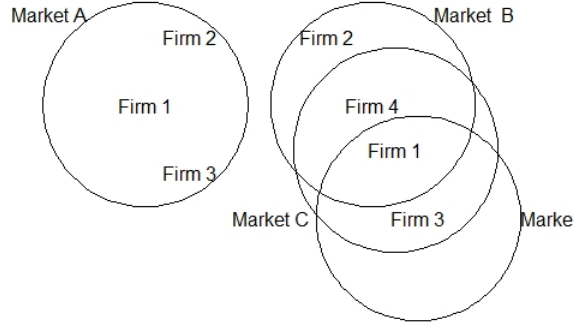


Figure 5: How to Calculate AVMMC

**AVMMC2** Since AVMMC may face issues of double counting in other markets, the second measure AVMMC2 is adopted. When calculating AVMMC2 for firm  $i$  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 at 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 at market A is 0.5 since firm 1 only has a contact with firm 3 in market C (AVMMC2 =0.5).

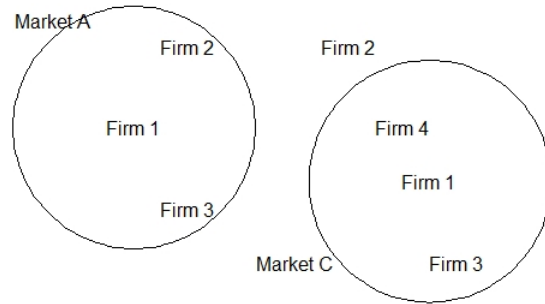


Figure 6: How to Calculat AVMMC2

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  $k$ th nearest neighbor approach as well as measuring market concentration. Second, I assume a hotel brand is considered as a single firm, consistent with Fernandez and Marin (1998) and Silva (2015).

### 3.6 Descriptive Statistics

Table 3 shows the descriptive statistics of the variables used in this paper. The first panel shows the variables commonly used, regardless of the market definition. The second panel represents variables created under the distance band approach, while the third panel shows the ones under the  $k$ th nearest neighbor approach.

As mentioned earlier, I assign the measures of MMC zero for independent hotels (non-branded hotels) so there are many observations with zero AVMMC and AVMMC2. 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  $k$ th nearest neighbor approach only considers the four nearest hotels as rivals in a market.

Table 3: Descriptive Statics of Key variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Price	1,880	85.849	52.001	16.990	44.512	118.453	400.750
No. of Room Sold	1,880	9,460	10,004	300	3,031	11,239	114,480
Room	1,880	111.690	117.694	6	37	131	1,200
Rating	1,880	1.763	1.659	0	0	3	6
No. of the same brand hotels	1,880	5.166	5.154	0	0	9	20
No. of the same chain hotels	1,880	18.226	18.375	0	0	34	55
Distance Band							
No. of rivals	1,880	20.755	10.918	1	13	29	46
AVMMC	1,880	26.689	29.279	0	0	46.1	132
AVMMC2	1,880	1.192	1.334	0	0	2	9
HHI	1,880	0.138	0.119	0.038	0.081	0.148	1.000
No. of the same brand in market	1,880	0.070	0.294	0	0	0	3
No. of the same chain in market	1,880	0.853	1.412	0	0	1	7
Kth Nearest Neighbor							
AVMMC.KNN	1,880	4.165	7.279	0	0	5	51
AVMMC2.KNN	1,880	0.917	1.725	0	0	1	12
No. of the same brand in market	1,880	0.011	0.105	0	0	0	1
No. of the same chain in market	1,880	0.183	0.387	0	0	0	1

## 4 Estimation and Model

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

$$P_{imt} = \alpha_1 MMC_{imt} + \beta X_{imt} + \epsilon_{imt} \quad (9)$$

where  $X_{imt}$  represents product characteristics of firm  $i$  in market  $m$  at period  $t$ , including the number of rooms and hotel ratings, and the indicator variables of the presence in the central business district (CBD) or the 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 the reduced form models: prices and multimarket contacts. Since reduced form models regress prices on the measures of MMC, the only endogenous variable concerned is MMC. This variable is highly affected by entry and exit decisions of the firms since the market structures in focal markets as well as other markets determine the multimarket contact. Thus, valid instruments should be correlated with the entry and exit decisions. This paper uses two sets of variables affecting the entry and exit decision: scale of the hotel (i.e., how many hotels a hotel brand operate) 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 operate, or how many hotels with different brands a hotel chain operate).

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 large scales, hotel brands can lower input costs by negotiating providers of the inputs and sharing operational expenses, including advertising. Franchisors (hotel brands) are likely to add more units in a market when expecting these benefits due to scale. Similar to Kosová et al. (2011), this paper uses the number of hotels under the same brand in the focal market and the number of hotels under the same brand within a city to measure the scale of a hotel brand.

Second, the scope of a hotel chain also affects entry and exit decisions of individual brands and consequently influence 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 in 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 scopes of hotel chains reduce 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 through spillover effects from the reputation of the signature brands.<sup>7</sup> Similar to cost saving due to the large scale of a hotel brand, hotel chains with large scopes 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.

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<sup>7</sup>Some hotel brands, such as Courtyard by Marriott and Four Points by Sheraton, use the reputation of signature brands in the hotel chain.

## 5 Results

Tables 4 and 5 summarize the estimation results of the IV 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 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).

Depending on the market definition, or the measures of MMC, the economics 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 of AVMMC raises prices by  $\$6.998 = 0.239 \times 29.279$ . Similarly, one standard deviation increase in AVMMC2 makes prices higher by  $\$6.932 = 5.197 \times 1.334$ . Both cases show similar increased prices due to one standard deviation increases in the measures of MMC.

In Table 5, 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  $k$ th nearest neighbor approach increase slightly greater than with distance band approach is that a firm can be more sensitive to small sets of the closest rivals.

Table 4: Estimation under the Distance Band Approach

	<i>Dependent variable:</i>	
	Price	
	(1)	(2)
AVMMC	0.239*** (0.037)	
AVMMC2		5.197*** (0.777)
Rating	25.954*** (0.677)	26.174*** (0.666)
No. of Room	0.011 (0.007)	0.012 (0.007)
HHI	-27.286*** (6.215)	-31.358*** (6.192)
CBD	48.975*** (3.421)	47.959*** (3.367)
AIR	-13.458*** (3.737)	-12.631*** (3.709)
Dummy of Quarter 2	5.264** (2.085)	5.352*** (2.072)
Dummy of Quarter 3	-0.987 (2.080)	-0.795 (2.067)
Dummy of Quarter 4	1.374 (2.075)	1.524 (2.061)
Constant	21.120*** (2.707)	21.212*** (2.654)
Observations	1,274	1,274
R <sup>2</sup>	0.714	0.717
Adjusted R <sup>2</sup>	0.712	0.715

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 5: Estimation under the KNN approach

	<i>Dependent variable:</i>	
	Price	
	(1)	(2)
AVMMC.KNN	1.179*** (0.200)	
AVMMC2.KNN		4.993*** (0.838)
Rating	28.543*** (0.762)	28.467*** (0.758)
No. of Room	0.008 (0.008)	0.007 (0.008)
HHI	-10.881 (10.869)	-13.214 (10.958)
CBD	46.731*** (3.627)	47.051*** (3.641)
AIR	-10.112** (4.014)	-9.988** (4.026)
Dummy of Quarter 2	5.217** (2.246)	5.164** (2.252)
Dummy of Quarter 3	-1.150 (2.241)	-1.207 (2.247)
Dummy of Quarter 4	1.289 (2.236)	1.170 (2.242)
Constant	16.750*** (4.121)	18.175*** (4.027)
Observations	1,274	1,274
R <sup>2</sup>	0.668	0.666
Adjusted R <sup>2</sup>	0.665	0.664
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01		

## 6 Conclusion

Using the hotel industry in Houston, TX, this paper examines the effect of multimarket contact on price. Metropolitan areas, like Houston, are valid geographic areas to test this hypothesis since hotel brands have multiple units throughout the cities and face similar sets of rivals across markets. Due to difficulty in defining valid markets in these cities, prior studies use samples where markets are clearly defined, or use the third-party defined market definition. This paper solves this problem empirically by using the distance metric approach by Pinkse et al. (2002). With this approach, the paper finds 2.5 miles and the 4 nearest neighbors of a hotel are valid market definitions for hotels in Houston, TX. With these empirically defined markets, this paper estimates the effect of MMC on prices and finds empirical support that multimarket contact facilitate higher prices, and confirms collusive behavior via multimarket contacts.

This paper has several limitations. First, a hotel brand is considered as a single firm, consistent with prior studies. However, a single hotel brand is likely to be part of the brand portfolio of a hotel chain. It would be interesting if this existence of multi-brand chain is considered. Second, this paper considers distance as the only factor which defines markets. Even though this approach is valid in the sense that hotels tend to have similar product characteristics depending on their locations, competition between hotels can be limited to hotels of similar ratings. It would be interesting if this type of competition is taken into account.



# Appendix

## A Additional Market Definition: Clustering Analysis

### A.1 Density based spatial clustering and application with noise(DBSCAN)

In this section, I provide an alternative approach of defining markets where firms are spatially distributed. I adopt one of the clustering methods – the one sorting an observation in a cluster in which observations show similar characteristics. I use density based spatial clustering and application with noises (DBSCAN). This approach define clusters by the number of points (observations) close to a given point. To use this approach, I need to determine the minimum number of points in each cluster (minPts) and the distance limit for each cluster (E, or esp) Given a point  $i$ , a radius neighborhood is defined by eps. With this neighborhood, if there are more than minPts, the point is considered as a core point and then forms a cluster. Other points in the cluster will be considered as border points. If any border points have more points than minPts with their own neighbors, they are considered as core points and additional clusters are created. Since these clusters are close enough, they are combined into one cluster. Any other points (neither core nor border) will be considered as noise.

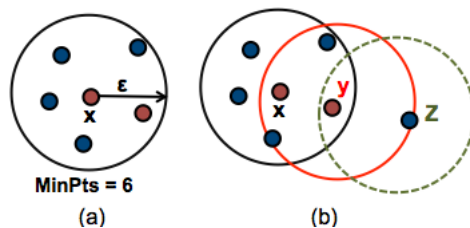


Figure 7: Caption

#### A.1.1 DBSCAN for the Houston Hotel Market (2014)

Since DBSCAN requires two pre-determined parameters (eps and minPts), I explain how these two parameters are determined.

- minPts: Hotels, in general, consider 4 to 5 hotels as major competitors in the local market (Kalnins, 2006). Based on this, I choose four for minPts. In addition, if minPts is greater than 4, there would not be significant difference in clustering results.
- eps: Given minPts = 4, I create a plot of the distributions of distances to the four nearest hotels(points) for each hotel by using the data set of hotels in Houston, TX in the first quarter in 2014. This plot is called the  $k$ NN distance plots. Since there are about 470 hotels per quarter, the number of distances calculated in this plot is about 1,880. Most of the distances are included between distance = 0 and distance = 0.02. Thus, setting eps for this analysis as 0.02 is reasonable since with this eps, I includes most hotels (points) as core or border points.

Based on the parameter values determined earlier(eps= 0.02, minPts = 4), I conduct clustering using DBSCAN.

The results of the clustering are summarized in the following figure and table. In sum, for each quarter, 21 clusters are created with 58 noise points (the ones that do not belong to any clusters)

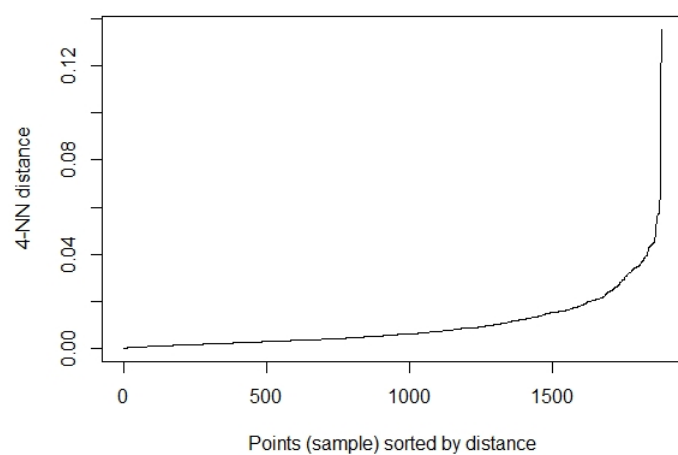


Figure 8: Estimate eps in the  $k$ NN approach

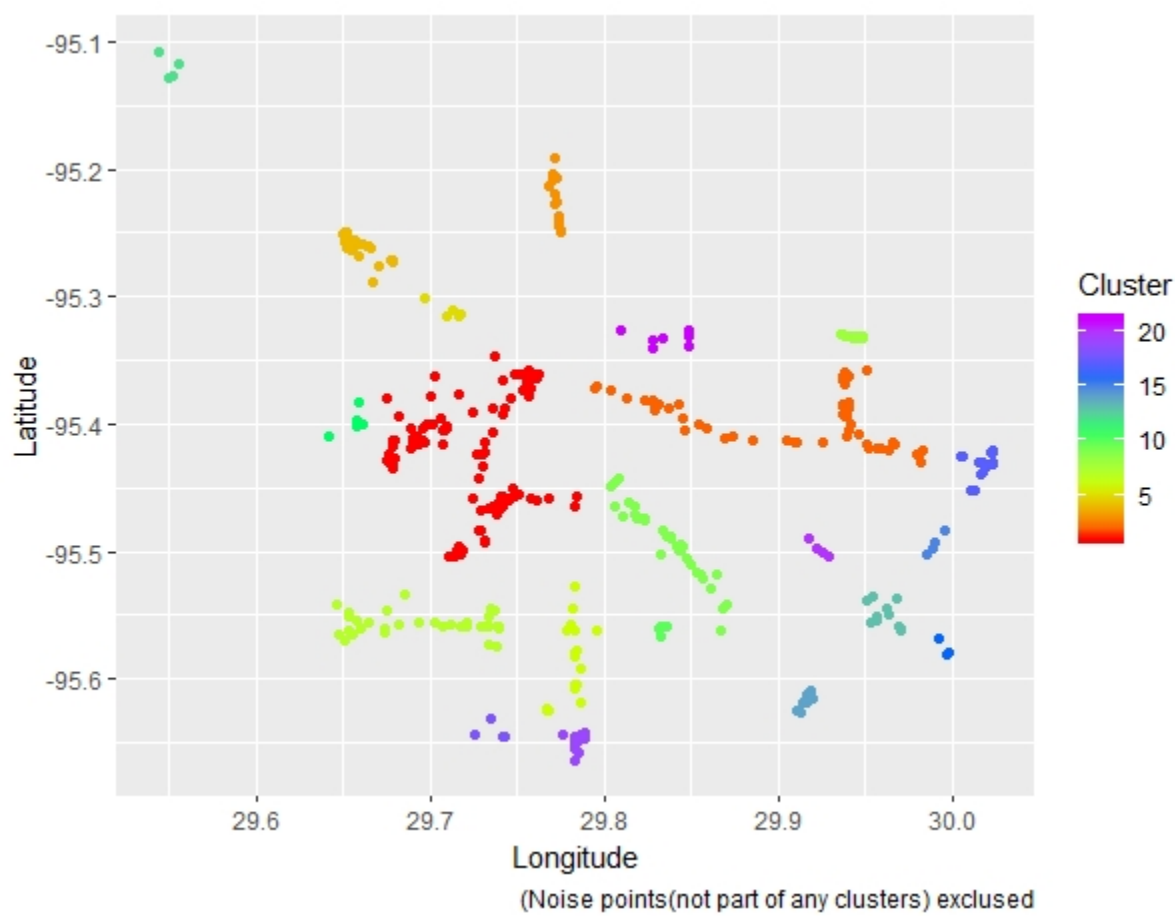


Figure 9: Results of DBSCAN Clustering

### A.1.2 Estimation under DBSCAN

Table 6: Descriptive Statistics under DBSCAN

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
AVMMC.CL	1,880	0.616	0.736	0	0	1.0	4
No. of the same brand in market	1,880	1.055	1.160	0	0	1	5
No. of the same chain in market	1,880	2.555	3.482	0	0	4	16

Table 7: Estimation under the DBSCAN approach

	<i>Dependent variable:</i>	
	Price	
	<i>OLS</i>	<i>IV</i>
	(1)	(2)
AVMMC.CL	7.789*** (1.119)	0.742 (14.832)
Rating	26.852*** (0.699)	26.925*** (0.727)
No. of Room	−0.001 (0.007)	−0.005 (0.012)
HHI	−37.201** (15.929)	−38.331** (16.377)
CBD	48.535*** (3.554)	47.891*** (3.860)
AIR	−10.222*** (3.758)	−11.055*** (4.204)
Dummy of Quarter 2	5.255** (2.210)	5.207** (2.251)
Dummy of Quarter 3	0.258 (2.334)	0.197 (2.378)
Dummy of Quarter 4	4.581* (2.699)	4.842* (2.800)
Constant	21.341*** (2.655)	29.046* (16.392)
Observations	1,148	1,148
R <sup>2</sup>	0.717	0.707
Adjusted R <sup>2</sup>	0.715	0.705

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 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., 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.
- Chung, W. and A. Kalnins (2001). Agglomeration effects and performance: A test of the texas lodging industry. *Strategic Management Journal* 22(10), 969–988.
- 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.
- 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 (1997). 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*.

- 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.
- Moncarz, E. S. (1984). Franchising in the hospitality industry: Accounting aspects. *Hospitality Review* 2(2), 7.
- Perrigot, R., G. Basset, and B. Meiseberg (2016). Resale prices in franchising: insights from franchisee perspectives. *Journal of Product & Brand Management* 25(7), 663–675.
- Pinkse, J., M. E. Slade, and C. Brett (2002). Spatial price competition: a semiparametric approach. *Econometrica* 70(3), 1111–1153.
- 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).