Essays on Franchising in the Service Industry

Item Type	Dissertation (Open Access)
Authors	Koh, Jung Hwan
DOI	10.7275/24277314
Download date	2025-09-08 21:41:18
Link to Item	https://hdl.handle.net/20.500.14394/18671

ESSAYS ON FRANCHISING IN THE SERVICE INDUSTRY

A Dissertation Presented

by

JUNG HWAN KOH

Submitted to the Graduate School of the
University of Massachusetts Amherst in partial fulfillment
of the requirements for the degree of

DOCTOR OF PHILOSOPHY

September 2021

Department of Resource Economics

© Copyright by Jung Hwan Koh 2021

All Rights Reserved

ESSAYS ON FRANCHISING IN THE SERVICE INDUSTRY

A Dissertation Presented

by

JUNG HWAN KOH

Approved as to style and content by:

Christian Rojas, Chair

Debi Prasad Mohapatra, Member

Albert Assaf, Member

John Spraggon, Department Chair
Resource Economics

Dedication

To Eun Jin, Hayden, and Leo

ACKNOWLEDGMENTS

Throughout the writing of the dissertation I have received a great deal of support and assistance.

I would like to thank my advisor, Christian Rojas, whose expertise and knowledge were invaluable in formulating my research questions and conducting empirical analysis. His insightful feedback and consistent support encouraged me to sharpen my thought and to take my work to the next level.

I would like to acknowledge my committee members, Debi Prasad Mohapatra and Albert Assaf, for their valuable guidance and support throughout my studies. I would also like to thank the faculty members in my department, John Sprragon, Daniel A. Lass, and Bernard Morzuch, for their encouragement and for all of the opportunities I was given in my department.

I would like to express my appreciation to my colleagues who made my time at Amherst enjoyable and memorable. I have also received tremendous support from my department, especially, Sophie Williamson and Eileen Keegan; their kind support made my academic life go smoothly.

Finally, I would like to thank my family for their continuous support during my studies. My children, Hayden and Leo, have provided necessary and excellent breaks from my work and have motivated me to complete my dissertation. My wife, Jina, has been supportive of me throughout my entire studies and has made countless sacrifices to help me get where I am. Without them, I doubt I would be in this place today.

ABSTRACT

ESSAY ON FRANCHISING IN THE SERVICE INDUSTRY

SEPTEMBER 2021

Jung Hwan Koh

B.B.A, KYUNG HEE UNIVERSITY

M.S., PURDUE UNIVERSITY

Ph.D., UNIVERSITY OF MASSACHUSETTS AMHERST

Directed by: Christian Rojas

In this dissertation, I explore behavior of firms in franchising, a form of vertical structure that lies between vertical integration (a single firm) and vertical separation (separate firms). Even though franchising contracts outline legal terms and conditions for franchisees (downstream firms) and obligations for franchisors (upstream firms), conflicts between these two parties can arise due to information asymmetries and principal-agency problems. Rather than analyzing these problems, I explore specific conditions in which either a franchisee or a franchisor can exercise more control over the other party and thereby increase its profits. Specifically, I examine the role that: a) multi-unit ownership plays on franchisees' market power, and b) multi-market contact plays franchisors' ability to engage in supra-competitive pricing.

The first chapter explores the effect of multi-unit ownership in isolated markets (low and mid-scale hotels near highway exits in Texas). I refer to multi-ownership operation to the case when a franchisee operates more than one hotel (either under the same brand or under different brands). Due to the distance to their franchisors, franchisees in these markets are likely to have more control over operations; in other words, the standardized management that is common in franchising may not be enforced with the same intensity. Using demand estimation of a random coefficient model of demand and counterfactual analyses, I find that franchisees who engage in multi-ownership exert more market power which, in turn, leads to higher prices. The second chapter investigates how multimarket contact between franchisors may facilitate collusive pricing. I focus on competition within a large metropolitan statistical area (MSA) where hotels face the same rivals across different geographic markets within the MSA. I contribute to the literature in two ways. First, I use clustering algorithms to delineate the mutually exclusive markets within the MSA. Second, I consider and estimate the degree to which upstream firms' control downstream pricing. Using a structural approach, I find evidence that supports the notion that multimarket contact enhances supracompetitive pricing and that modeling (rather than assuming) the degree of vertical control plays a key role in the estimation.

TABLE OF CONTENTS

ACKNOWLEDGMENTS v

ABSTRACT vi

LIST OF TABLES x

LIST OF FIGURES xi

CHAPTER

1. MULTI-UNIT OWNERSHIP AND MARKET POWER: A STUDY OF THE LODGING INDUSTRY IN TEXAS 1

- 1.1 Introduction 1
- 1.2 Literature Review 6
- 1.3 The U.S. Lodging Industry and Multi-Unit Ownership 9
- 1.4 Model 12
  - 1.4.1 Demand 12
  - 1.4.2 Supply 14
  - 1.4.3 Consumer Welfare 16
- 1.5 Data and Estimation 17
  - 1.5.1 Data 17
  - 1.5.2 Estimation 20
- 1.6 Estimated Results 23
  - 1.6.1 Preliminary Analysis: The effect of Multi-Unit Ownership on Prices 23
  - 1.6.2 Demand Estimates 26
  - 1.6.3 Counterfactual Analysis 29
- 1.7 Conclusion 34

2. MULTIMARKET CONTACT, PRICING, AND FRANCHISING: A STUDY OF THE HOTEL INDUSTRY IN TEXAS 38

- 2.1 Introduction 38
- 2.2 Literature Review 41
- 2.3 Data 46
  - 2.3.1 Data Source 46
  - 2.3.2 Market Definition: Clustering Approach 47
  - 2.3.3 Measures of Multimarket Contact 49
  - 2.3.4 Descriptive Statistics 51

2.4 Model and Estimation Details 54
  2.4.1 Reduced Form Model 54
  2.4.2 Structural Model 54

2.5 Results 62
  2.5.1 Reduced Form Models 62
  2.5.2 Structural Models 63

2.6 Conclusion 68

APPENDICES

A. Appendix for Chapter 1 71
  A.1 Multi-Unit Owners in Texas 71
  A.2 Variable Definitions 73
  A.3 Results of the First Stage Regression 74

B. Appendix for Chapter 2 75
  B.1 Analysis of Franchise Disclosure Documents 75
  B.2 Robustness Check of Market Definition: Distance Metric Approach 82
    B.2.1 An Issue with the Distance Metric Approach 84
    B.2.2 Firm Specific Measures of MMC 86
    B.2.3 Descriptive Statistics of Key Variable Under the Distance Metric Approach 89
    B.2.4 Results of Reduced Form Models 89

BIBLIOGRAPHY. 91

LIST OF TABLES

Table Page

1 Descriptive Statistics of Key Variables 20
2 Multi-Unit Ownership (All Markets) 24
3 Hotel Characteristics in Markets with Multi-Unit Ownership 24
4 Effect of Multi-Unit Ownership (Market Structure) on Prices 26
5 Results of Demand Estimation 27
6 Descriptive Statistics of Marginal Costs and Markups 28
7 Changes in Prices and Market Share in Counterfactual Analysis . . . 31
8 Additional Counterfactual Analysis with Different MC 32
1.1 Changes in Prices($p*$) with Different Marginal Costs 32
9 Descriptive Statistics of Key Variables 51
10 Results of Reduced Form Model 63
11 Results of Demand Estimation 64
12 Results of Supply Side Estimation 65
13 Estimated Conduct Parameters 66
14 Set Up For Conduct Parameters for Counterfactual Analysis 67
15 Comparison of Average Observed Prices and Equilibrium Prices . . . 67
16 Multi-Unit Owners in Different Market Definitions 71
17 Market Size by Market Types 72
18 Descriptive Statistics by Ownership Types in All Markets 72
19 Descriptive Statistics of Owners in Markets with Multi-Unit Owners . 72
20 Variable Descriptions 73
21 Results of First Stage Regression 74
B.1 Revenue Management System and Consulting Service 78
22 Price Reaction Function Estimation 84
23 Descriptive Statistics of Key Variables 89
24 Estimation Under Distance Metric Approach 90

LIST OF FIGURES

Figure Page

1 Ownership Types in Franchising 2
2 Remote Market Near Interstate Highways in Texas 18
3 Example of A Remote Market Near I-10: Kerrville in Texas 19
4 Distribution of Own Price Elasticities 28
5 Marginal Costs 29
6 Markups 30
7 Various Marginal Cost Assumptions 33
8 Price Variations 34
9 Changes in Average CVs with Different Marginal Costs 35
10 Distribution of Distance from the Fourth Nearest Neighbor (2014 Q1) 49
11 Clusters of Houston, TX (2014 Q1) 53
12 Distribution of MMC_{jk} for Branded Hotels 53
13 Changes in Price Under Model 2 68
14 Change in Prices Under Model 3 69
15 Price Effects (Changes in Distance) 85
16 Double Counting 85
17 Indirect Effects 86
18 How to Calculate AVMMC 87
19 How to Calculate AVMMC2 88

CHAPTER 1

MULTI-UNIT OWNERSHIP AND MARKET POWER: A STUDY OF THE LODGING INDUSTRY IN TEXAS

1.1 Introduction

Franchising is one of the widely used business governance formats in the U.S. retail and service industries. In a franchising contract, franchisees sell franchisors' products or use their brand names (trademarks), or managerial skills at a given location for a certain period time by paying initial installments (franchise fees) in addition to sales-based fees (royalties). With franchising contracts, franchisors can grow by adding more units, or stores under their franchise system with less capital investments. With initial and ongoing support from franchisors, franchisees can take advantage of established management skills, or national/regional marketing campaigns that are not possible for individual franchisees to achieve otherwise. As franchisees become experienced and more efficient in their operation in their local markets, some franchisees tend to expand their business by owning additional units under the same franchisor. This is known as multi-unit franchising and this type of owners are called as *multi-unit franchisees.* Multi-unit franchising are not rare, although the majority of franchisees remain single unit owners. Various studies in franchising show the prevalence of multi-unit franchisees. Kalnins and Lafontaine

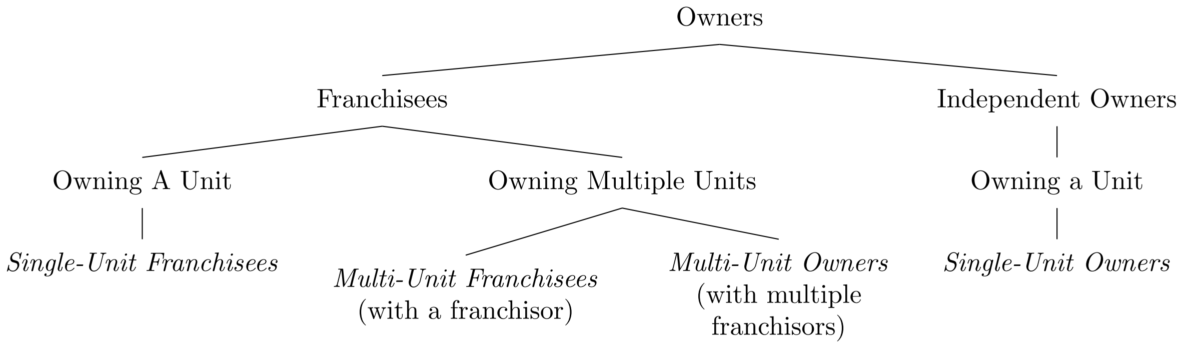
Owners
Franchisees
Independent Owners
Owning A Unit
Owning Multiple Units
Owning a Unit
Single-Unit Franchisees
Multi-Unit Franchisees (with a franchisor)
Multi-Unit Owners (with multiple franchisors)
Single-Unit Owners

Figure 1: Ownership Types in Franchising

(2004) indicate that among franchised units of the seven major fast food chains in Texas in 1995, 49% of franchisees operated more than one unit; these owners accounted for 84% of total franchised units in the fast food chains.

In addition to multi-unit franchising, some of these franchisees own units affiliated with multiple franchisors due to weak exclusive clauses in franchising contracts (Blair and Lafontaine, 2005; Wilson, 2011). In this paper, these owners are referred as *multi-unit owners*. Figure 1 summarizes the types of ownership in the context of franchising. As local business owners, franchisees can be sort into two categorized by whether owning (or operating) one unit or more than one unit. If franchisees own a single unit, they are considered *single-unit franchisees* or *single-unit owners* in this paper. If franchisees own more than one unit, they are sorted into either *multi-unit franchisees*, franchisees with multiple units who have franchising contracts with a single franchisor, or *multi-unit owners*, franchisees with multiple units who have franchising contracts with different franchisors.[1]

Traditional theories of franchising, which consider transaction costs and agency-based frameworks, cannot explain also the emergence and prevalence of this type of ownership in franchising. Agency-based frameworks suggest franchising is beneficial since the costs of the separation between owners and operators are minimized: as residual claimers, franchisees have an economic incentive to invest more effort than managers hired by franchisors. As owners of franchised units add more units, however, this advantage would disappear since the franchisees might start to manage multiple units by hiring managers at their units In addition, if multi-unit owners are affiliated with multiple franchisors, these owners would have more control in operation and management, making franchisors face higher costs of monitoring and controls over these franchisees.

---

[1] This paper focuses on analyzing multi-unit owners since majority franchisees with multiple units in the data set are multi-unit owners. In my data set, out of 240 hotels owned by franchises operating more than one unit, only 2 hotels are owned by a multi-unit franchisee.

The transaction-cost perspective provides reasonable arguments for multi-unit franchising but not for franchisees associated with multiple franchisors (multi-unit owners). In multi-unit franchising, franchisors can reduce transaction costs, such as monitoring, or training costs with multi-unit franchisees since these franchisees are more experienced and tend to invest more efforts/funds than single-unit owners. However, it is not clear that franchisors can reduce such transaction costs if franchisees have franchising contracts with multiple franchisors.

Rather than relying on the classic literature that explains franchising structurally, this paper explores whether a framework of market power helps explain why franchisees are affiliated with multiple franchisors. Specifically, I empirically test how multi-unit ownership affects market outcomes, focusing on how multi-unit owners exercise market power. The lodging industry is suited to the evaluation of multi-unit ownership for several reasons. First, in the lodging industry franchising is one of the widely used business formats, and multi-unit owners are prevalent; futher, some of these owners are affiliated with more than one franchisor in this industry (Kalnins, 2006). Multi-unit ownership is also observed in small geographic markets in this industry since hotels tend to cluster together in small areas where consumer demand is high, such as central business districts and tourist destinations. Hotel chains with multiple brands tend to operate multiple hotels in these small markets, while owners are likely to own more than one hotel under either the same or, different hotel chains.

I use data on hotels and motels near interstate highway exits in Texas, where hotels tend to be closely located near exits, thereby creating distinct clusters away from other geographic markets. In these clusters, as opposed to metropolitan areas, franchisees have strong control over their operational and pricing decisions. This results from franchisees being distant from the national/regional headquarters of the franchisors. Another reason is that franchisors of economy/budget, or midscale hotel brands (low to medium quality brands, which are typically found near highway exits) tend to provide discretion to franchisees. Therefore, the franchisees in the markets I study are likely to have more control on management and pricing decisions. Given these conditions, this paper focuses on franchisees that have minimal influence from franchisors. In order to analyze the behavior of franchisees, it is required to identify the owners of individual hotels in the markets. I use data on hotel occupancy taxes from the Texas Comptroller's Office, matching information on each taxpayer with hotel data.

To measure the market power of multi-unit owners in these markets, I adapt the approach of Berry et al. (1995). First, a random coefficient logit model is used to estimate demand parameters. With the estimated demand parameters, marginal costs are recovered under an assumption on the supply side: firms jointly maximize profits across their units (the pre-scenario). Using demand estimates and the recovered marginal costs, I conduct a counterfactual analysis in which all franchisees are assumed to be single-unit owners (the post-scenario). Comparison between the pre- and post-scenarios allows testing whether multi-unit owners exercise market power. The results of this paper show that firms with multi-units charge higher prices, supporting the hypothesis that multi-unit ownership associated with multiple franchisors implies the exercise of market power. In addition, without multi-unit ownership, market shares and therefore volume (rooms sold), on average, would increase, thereby improving consumer welfare.

This paper is one of the first papers to analyze the effects of multi-unit ownership using a structural approach. Most studies in the franchising literature have only focused on the issues of multi-unit franchising, even though there is evidence that franchisees associated with multiple franchisors are common in various industries, such as hotel and restaurant ones (Blair and Lafontaine, 2005). Using data on taxpayer information from hotel occupancy tax receipts, I separate upstream (franchisors) and downstream(franchisees) firms, and then analyze the effects of the behavior of the downstream firms. Moreover, I limit the sample of this paper to hotels and motels near the interstate highway exits in Texas to minimize the possibilities that franchisors have strong controls over day-to-day operation, or pricing at their franchised hotels.[2]. Another benefit of choosing these remote markets is that it allows for a straightforward definition of markets, thereby circumventing the possibilities of cross-market competition (i.e., a hotel in a highway exits is unlikely to compete with other hotels at other, distant, exits.).

The rest of the paper proceeds as follows: Section 1.2 reviews the relevant literature. Section 1.3 discusses the multi-unit ownership in franchising and the characteristics of the U. S. hotel industry in the current study. Section 1.4 presents the models of demand estimation and counterfactual analysis. Section 1.5 summarizes the data and estimation strategies. Section 1.6 covers the results of the demand estimation and the counterfactual analysis. Section 1.7 concludes the paper.

---

[2] Major hotel chains tend to have strong control over franchised hotels in larger markets, such as metropolitan areas through regional quality control, or revenue managers.

1.2 Literature Review

Most studies in the literature on franchising have viewed franchising to represent a type of organization that lies somewhat between vertical separation and vertical integration (e.g., Lafontaine (1992); Dahlstrom and Nygaard (1999); Blair and Lafontaine (2005)). These studies have examined conflicts, incentive alignment, control, or monitoring over other parties between upstream and downstream firms using a classical theoretical framework of franchising, such as transaction costs (e.g., Dahlstrom and Nygaard (1999)) and agency cost theories (e.g., Kidwell et al. (2007)). In addition, the majority of empirical studies in economics and management focus on franchisors' decisions – double distribution channels (corporate owning and franchising), and optimal franchising proportions – while only a handful of studies analyze the decisions of local owners or franchisees. The majority of these latter studies analyze the trade-offs between being independent and being franchised units from the viewpoint of franchisees (e.g., Mazzeo, 2004; Kosová et al., 2011, 2013; Chaudey and Fadairo, 2008).

Rather than relying on these theoretical frameworks, this paper focuses on cases in which franchisees have more discretion in day-to-day operations and management, with less control from franchisors. These cases are considered to be closer to vertical separation. With this setup, this paper analyzes franchisees' behaviors.

The findings of this paper are consistent with the literature on multi-unit franchising (Kalnins and Lafontaine, 2004; Thomadsen, 2005), entry/exit (Davis, 2006a; Kalnins, 2004b; Mazzeo, 2002b) and brand proliferation (Wilson, 2011). Using Texas fast food chains as a sample, Kalnins and Lafontaine (2004) show that units owned by multi-unit franchisees are close to each other, or are located in demographically similar markets. This enables multi-unit franchisees to transfer local knowledge and experience across their units. Thomadsen (2005) simulates counterfactual analysis: mergers between units of fast food chains in small geographic markets. His results show that simulated mergers increase prices, similar to my results. His analysis focuses only on multi-unit franchisees, excluding the presence of franchisees with multiple units associated with franchisors in the markets.

In the literature on encroachment and entry/exit, Kalnins (2004b) finds empirical evidence for why franchisees have contracts with different franchisors. He shows that cannibalization effects (revenue reduction by entry of firms with the same brands) are greater than business-stealing effects (revenue reduction by entry of firms with different brands) in the Texas hotel industry, supporting the notion that franchisees associated with different franchisors generate positive benefits. However, Kalnins, without considering the role of the hotel owners, assumes that hotel franchisors, in general multi-brand firms, make the entry/exit decisions. Using detailed information on the identity of individual hotels, this paper incorporates the multi-unit and multi-franchisor system in a structural approach.

Similar to Kalnins (2004b), Wilson (2011) analyzes the effect of brand proliferation of hotel chains from the viewpoints of franchisors. Wilson finds that revenue reductions due to new entrants do occur, but the magnitude of these reductions is smaller if the entry is made by different branded hotels under the same hotel chain, or by branded hotels under the different chains. He also examines the effect of multi-unit ownership by using a reduced-form model, but the results are insignificant, which might be driven by insufficient data. I circumvent this issue by incorporating several data sets and employing a structural approach.

Even though multi-unit franchising and multi-franchisor are prevalent in many industries, few studies have empirically analyzed the effect of multi-unit ownership in the context of franchising. Kalnins and Mayer (2004) employ survival analysis to franchised units of fast food chains in Texas. They find that multi-unit franchising lowers failure rates if owners accumulate local knowledge and experience and can transfer that knowledge to the operation/management of their units, or hotels. Moreover, Kalnins and Lafontaine (2004) argue that multi-unit franchising utilizes local specific knowledge of well-performing franchisees, reduces free-riding issues between franchisees (i.e., franchisees in the same market are not incentivized to invest similar efforts to maintain, or promote their brand). Moreover, with multi-unit franchisees in the same market, franchisors can avoid criticism from incumbent franchisees when new franchised units are added since the owners of these units are the same.

Kalnins (2004a) and Thomadsen (2005) show new units under multi-unit franchisees tend to be located close to existing units or in demographically similar markets. While these studies focus on knowledge transfer between units under the same ownership, this paper focuses on how multi-unit owners compete in the markets, providing a different view on the motivation of owning multiple units in local markets. One exception is Kalnins (2004a) who analyzes multi-market contacts between franchisees in fast food chains in Texas, rather than between franchisors. Since multi-unit franchisees have contact with other franchisees within and across franchisors, this creates possible conditions of mutual forbearance. Kalnins finds that in markets with high uncertainty, franchisors tend to assign new units to franchisees with higher levels of multi-market contacts. This effect of multi-market contacts requires analysis of multiple markets, which is beyond the within market competition approach of this paper.

Studies in entry and exit (or encroachment) are quite similar to this paper in that these studies examine the effects of inter- and intra-firm competitions (Davis, 2006b; Mazzeo, 2002a; Kalnins, 2004b). Even though these studies assume firms make decisions by taking into account strategic interactions among competitors, there is little consideration on the ownership structure at the local market level. Without considering ownership, it is hard to analyze competition unless firms are perfectly separated in a vertical structure.

1.3 The U.S. Lodging Industry and Multi-Unit Ownership

The U.S. lodging industry provides vertically and horizontally differentiated products. Although there are different ways to measure hotel quality at the brand or property levels, most hotels are rated by popular hotel rating systems (*AAA*, *TripAdvisor*, or major online travel agencies). These provide relatively consistent measures of product quality that consumers trust and can easily access before consumption. Major hotel chains also provide a range of hotel brands with different levels of quality. In some geographic areas, a hotel chain provides multiple hotels with different qualities, resulting in higher market concentration than if the hotels were owned by different chains (Mazzeo, 2002a; Kalnins, 2004b; Wilson, 2011).

In addition to vertical differentiation, hotels are differentiated by location, even within a geographic area (like cities). Depending on travel distances to tourist destinations or other preferred places, consumers may consider the same brand hotels to be different products. Also, hotels of the same brand can be perceived differently if they offer different sets of amenities, or services. Variations in these sets of amenities and services differentiate one hotel from the others, even within the same geographic area. Thus, hotels in metropolitan areas typically face only a limited set of competitors. For example, Kalnins (2006) shows that, on average, hotel managers recognize only four to five competitors in their markets. Thus, hotels face limited competition, thereby marking markets more likely to be oligopolies.

Agglomeration is a widely observed market phenomenon. Hotels tend to locate close to other competing hotels since consumer demand is high for staying close to desired destinations within a city. In these areas, hotels try to differentiate from other competitors, vertically or horizontally. Mazzeo (2002b) supports this notion for vertical differentiation of hotels and motels near highway exits in the United States. In addition, Kalnins (2004b) shows that if hotels face competition from other hotels that exhibit different product qualities, their revenues or profits are higher than if the competition comes from hotels of similar qualities.

Most branded hotels are under vertical contracts with their franchisors. As mentioned earlier, Franchising, one of the most popular forms of the vertical contracts, allows franchisees to use brand names, management formats, or centralized reservations systems, while paying to franchisors initial franchise and royalty fees.[3] The average length of a franchising contract in the lodging industry is about 20 years, which is longer than in other industries. Most franchisors have established their own centralized reservation systems and management standards to control the quality of products and services.

Franchising contracts are more prevalent among low- or mid-quality hotels since operations at these hotels are more standardized. Conversely, management contracts, another form of vertical contract, are more widely used by upscale hotels. Management contracts allow franchisees limited control over day-to-day hotel operations. On the other hand, franchisors, as operators of the hotels, supervise all operations. This is highly related to the complexity of operating upscale hotels and the difficulties of maintaining their service standards required by hotel chains.

---

[3] Franchise fees are a one-time lump sum payment due to franchisors when franchising contracts are signed. Royalty fees, ongoing payment to franchisors, are generally a combination of fixed and variable terms; the variable terms are normally based on volume sales.

Since this paper analyzes hotels near interstate highway exits, hotels have at most a three star rating out of the maximum five given by the standard *TripAdvisor*'s rating system. This is largely because demand for hotels near interstate highway exits is not enough to accommodate four to five star hotels. Thus, most branded hotels in these locations are likely to be under franchising contracts. Under franchising contracts, local hotel owners become residual claimants of revenues after paying the franchising and royalty fees to franchisors. Franchisees also have more control over their business, including pricing policies, while following the business standards set by the franchisors.

It is common in markets with high demand that a single hotel chain operates hotels under different brands to attract different types of travelers. This might create some conflicts between franchisors and franchisees, such as cannibalization effects (Kalnins, 2004b) and free-riding over other franchisees (Wilson, 2011).[4] To prevent these conflicts, most franchising contracts include exclusive clauses which prevents either franchisees or franchisors from engaging in any actions against their counter parties. Exclusive territory clauses grant franchisees the right to be the sole provider in a certain geographic area. Non-compete clauses, another type of exclusivity clauses frequently included in franchising contracts, prevents franchisees from engaging in similar businesses during and after the franchising contracts. However, these are negotiable or not strictly enforced in many cases (especially in the hotel industry). For example, if the franchised hotels locate in high demand markets, these terms might be loosened, allowing other franchisees to enter the market with the same or different brand names. If the franchisees are experienced and have accumulated local knowledge or relationship in a certain area, adding additional units by these franchisees would be beneficial for both franchisees and franchisors (called multi-unit franchising).

---

[4] Franchisees have less incentive to sustain the franchisors' quality standard while benefiting from good reputations from other franchisees or franchisors.

Multi-unit franchising has become more popular in service industries, especially in the restaurant industry (Blair and Lafontaine, 2005), while hotel owners tend to own single units due to financial constraints (Wilson, 2011). In general, franchisees tend to own both land and physical properties, including the building and equipment in rooms. These high initial costs may deter current hotel owners from adding new units (hotels). However, as management of the low- or medium- quality hotels across hotel chains has become more standardized, it is increasingly more common to see local hotel owners add additional units in the same market or geographically close markets. For example, this paper finds that 240 hotels out of 5,186 hotels located near the interstate highway exits in Texas were owned by franchisees with more than one unit. While this figure suggests that multi-unit ownership might not be widespread, my estimates suggest their economic effect is not negligible.

1.4 Model

1.4.1 Demand

To estimate demand, I use a random coefficient logit model, which allows for flexible substitution patterns by accounting for consumer heterogeneity in preferences over product characteristics (Berry, 1994; Berry et al., 1995; Nevo, 2000).

The indirect utility of consumer i purchasing product j at market t is

$$u_{ijt} = \alpha_i p_{jt} + X_{jt}\beta_i + \xi_{jt} + \epsilon_{jt}, \tag{1.1}$$

where p_{jt} is the price of product j in market t, X_{jt} represents observed product characteristics, including the distance to the highway exit, the number of activities, the number of room types, and the number of services provided for business travelers.[5] ξ_{jt} is an unobserved product characteristic, and ϵ_{ijt} is a random shock that is assumed to follow a type I extreme value distribution.

To control the characteristics of local markets, location fixed effects (highway exits) are included. In Equation (1.1), I assume that the coefficients of price and product characteristics (α_i and β_i) have normal distributions with an average preference, α and β, respectively, and idiosyncratic terms: $\sigma_p v_i^p$ and $\sigma_k v_i^k$. Term σ measures the standard deviation in consumer preference and v_i represents the idiosyncratic preference. Thus, the coefficients of prices and product characteristics are rewritten as: $\alpha_i = \alpha + \sigma_p v_i^p$ and $\beta_i = \beta + \sigma_k v_i^k$.

The utility of the outside option is

$$u_{i0t} = \xi_0 + \sigma_0 v_i^0 + \epsilon_{iot},$$

where the utility from the outside option is normalized to zero. This completes the specification of the utility function.

Given the assumptions of the random coefficients, the utility function can be divided into two parts: the mean utility and the deviation from the mean as follows:

$$u_{ijt} = \delta_{jt}(X_{jt}, p_{jt}, \xi_{jt}; \theta_1) + \mu_{ijt}(x_{jt}, p_{jt}, v_i; \theta_2) + \epsilon_{ijt}, \tag{1.2}$$

$$\delta_{jt} = \alpha p_{jt} + X_{jt}\beta + \xi_{jt},\ \mu_{ijt} = p_{jt}\sigma_i^p v_i^p + x_{jt}\sigma^k v_i^k. \tag{1.3}$$

where $\theta_1 = [\alpha, \beta]$ and $\theta_2 = [\sigma^p, \sigma^k]$. Based on the framework of McFadden (1989), the choice probability of individual i choosing j in market t is the following (under assumed distribution for ϵ_{ijt}):

---

[5] Hotel rating and hotel age were tested, but showed high correlation with other product attributes. Thus, these variables are excluded.

$$s_{ijt} = \frac{\exp(\delta_{jt} + \mu_{jt})}{1 + \sum_{l=1}^{j} \exp(\delta_{lt} + \mu_{lt})}.$$

Aggregating the probability of the individual consumer probabilities, market share can be written as:

$$s_{jt}(\delta, \theta) = \int s_{ijt} dF(v) = \int \frac{\exp(\delta_{jt} + \mu_{jt})}{1 + \sum_{l=1}^{j} \exp(\delta_{lt} + \mu_{lt})} dF(v). \tag{1.4}$$

There is no closed from solution for the integral in Equation (1.4), so this should be numerically approximated. This paper uses the Halton draw for numerical approximation, which creates lower simulation errors (Reynaert and Verboven, 2014; Brunner et al., 2017). The number of a draw is 5,000. With this set up, the estimated market shares can be obtained as follows:

$$s_{jt} = \frac{1}{NS} \sum_{i=1}^{NS} \frac{\exp(\delta_{jt} + \mu_{jt})}{1 + \sum_{l=1}^{j} \exp(\delta_{lt} + \mu_{lt})}. \tag{1.5}$$

1.4.2 Supply

I assume that firms play a Bertrand-Nash game by setting prices of their products to maximize their profits. The focus of this study is whether franchisees can exercise market power by owning multiple units. Even though it is interesting if I analyze the effect of multi-unit franchisees and multi-unit owners separately, it is infeasible due to insufficient data for multi-unit franchisees.[6] Thus, it is reasonable that I assume that all franchisees with multiple units are multi-unit owners, ones who are associated with multiple franchisors.

---

[6] In the data set of this paper, there is a multi-unit franchisee during one quarter out of twenty eight quarters, but this franchisees become multi-unit owners through have contracts with multiple franchisors for the rest of time periods

As explained earlier, I focus on franchisees in markets where franchisors have less control over their franchisees.[7] Since in my setup

Since in my setup franchisees have control over their decisions, the notion, *firms* in the markets refers to franchisees. If firms (franchisees) own multiple units (hotels), the firms jointly maximize their profits in setting prices of their units. Otherwise, single-unit firms (franchisees) set prices for their single-units. The profit function is as follows:

$$\max_{p_{jt}, j \in F_f} \pi_f = \sum_{j \in F_f} (p_{jt} - mc_{jt}) M_t s_{jt}(p) - C_f, \tag{1.6}$$

where firm f has product j in F_f(a set of products of firm f), mc_{jt} is the marginal cost, $s_j(p)$ is the market share of product j, M_t is the market size, and C_f is the fixed cost of firm f.

From the profit function, the first-order condition is derived and can be rewritten for the equation of markup in matrix form:

$$p - mc = [\Omega^{pre}]^{-1} s(p) \tag{1.7}$$

where

$$\Omega^{pre}_{j,h} = \begin{cases} -\partial s_j / \partial p_k & \text{if } j, k \in F_f \\ 0 & \text{otherwise.} \end{cases}$$

The ownership structure matrix, Ω captures the existence of multi-unit firms in the market. From Equation (2.15), the marginal costs are estimated as $\hat{mc} = p - \Omega^{pre} \cdot s(p)$. These marginal costs rely on demand estimates and the Bertrand-Nash assumption of the supply-side model. If the demand estimates or the assumptions of the supply side change, marginal costs would change accordingly. For the counterfactual analysis, I assume that marginal costs are constant. Later, I relax this assumption to check the robustness of the counterfactual analysis.

---

[7] To provide preliminary evidence on the market power hypothesis, I conduct reduced-form analysis in Section 6.

I conduct the counterfactual analysis using the demand estimates and the estimated marginal costs. New equilibrium prices under a counterfactual scenario in which all firms own single units are estimated as follows:

$$p^* = \hat{mc} + [\Omega^{post}]^{-1} s(p^*), \tag{1.8}$$

where $\hat{mc}$ represents the marginal costs estimated under the multi-unit ownership.

To obtain the equilibrium prices under the baseline post-scenario, I make two assumptions. First, the cost structures are the same under the pre- and the post-scenarios. As mentioned in Nevo's (2000) merger simulation analysis, multiple brand firms (or merged ones) could enjoy a cost efficiency. To allow for this possibility and to check for the robustness of the baseline specification, different assumptions on marginal costs are also considered. Second, to obtain Ω^{pre} and Ω^{post}, I use the same demand estimates, even though firms may change their product characteristics and consumers may shift their preferences (both observed and unobserved ones) depending on their market positions. However, both of these changes are rather long-run ones, while pricing decisions are short-run ones since hotels often change or update their prices daily. The paper assumes that these demand estimates are constant between the two scenarios.

1.4.3 Consumer Welfare

I use the compensating variation to capture the change in consumer welfare, which is calculated as follows:

$$CV_i = \frac{\ln[\sum_{j=0}^{J} \exp(V_{ij}^{post})] - \ln[\sum_{j=0}^{J} \exp(V_{ij}^{pre})]}{\alpha_i} \tag{1.9}$$

where $V_{ij} = \alpha_i p_j + X_j \beta_i + \xi_j$. When calculating V_{pre} and V_{post}, the price (p^{pre} and p^{post}) varies, while other components, including ξ_j, stay the same. The average CV at the market level is given by

$$CV_t = M_t \int CV_i dP_v(V) = M_t \cdot \frac{1}{ns} \sum_{i}^{ns} CV_i \tag{1.10}$$

where P_v is the distribution function of v. M_t is the market size at market t. Market size is the number of rooms sold in the market plus the number of consumers using outside goods. Since prices and market shares are daily based, to capture the annual level of consumer welfare, CV is converted to the annual level by multiplying by 365. The following results (changes in prices, CV at the market level, and others) are based on a sample of 116 markets with multi-unit owners.

1.5 Data and Estimation

1.5.1 Data

Data Sources Data for this paper is derived from three sources. First, prices, quantities, capacities (the number of rooms), and chain affiliation comes from the *Texas Hotel Performance Fact book* provided by Source Strategic, Inc, a Texas-based consulting firm. Second, taxpayer identification numbers, which are used to identify actual hotel owners, are collected from *Hotel Occupancy Tax* provided by the Texas Comptroller's Office. Third, amenities and services at hotels are collected from from *TripAdvisor*.

Market Definition The market definition used in this paper is rather narrow: Hotels located within a half-miles radius of an interstate exit in Texas.[8]. If hotels in

---

[8] The following interstate highways are included: I-10, I-20, I-27, I-30, I-35, I-45, and I-40

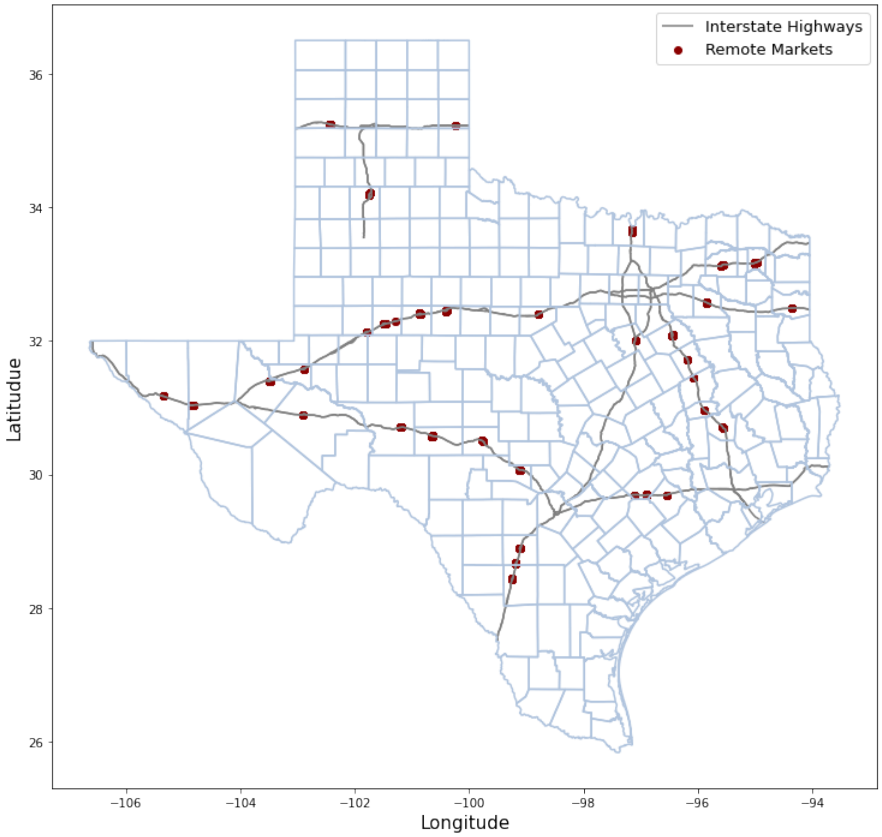

Figure 2: Remote Market Near Interstate Highways in Texas

one exit are close to other exits, or if hotels are located in metropolitan areas, they are excluded from the analysis (See Figure 2). Thus, markets and sample hotels chosen by these criteria are remote and narrow, compared to geographic markets in metropolitan areas (See Figure 3).

Even though the sample might not be a perfect representation of all multi-unit owners in Texas, using this restricted definition of markets creates two major advantages. First, with this definition, the study minimizes the possibility of cross-market competition. Second, selecting these remote and isolated markets is consistent with the assumption that franchisees have more control over their pricing policies than franchisors. Since these hotels are far from the national/regional headquarters of their franchisors or other hotels under the same brand, franchisors face high con-

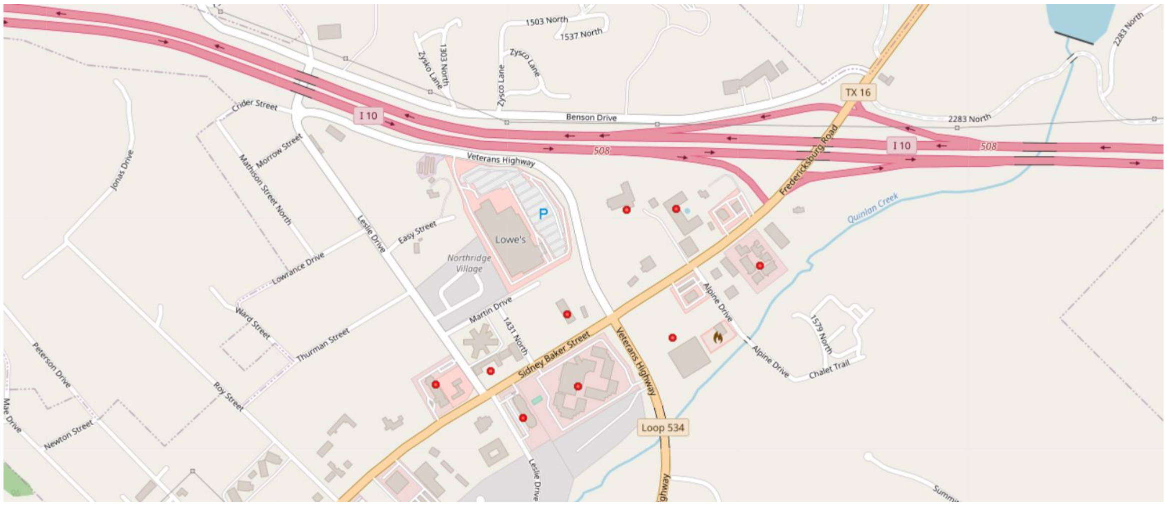
1503 North
1537 North
Zysko Lane
1303 North
Zysco Lane
Zysco Lane
Benson Drive
TX 16
2283 North
2283 North
Cider Street
I 10
Morrow Street
Mattison Street North
Veterans Highway
508
I 10
508
Fredericksburg Road
Jonas Drive
P
Lowe's
Quinlan Creek
Easy Street
Leslie Drive
Northridge Village
Lowrance Drive
Martin Drive
Alpine Drive
1579 North
Ward Street
Thurman Street
1431 North
Sidney Baker Street
Veterans Highway
Alpine Drive
Chalet Trail
Peterson Drive
Roy Street
Mae Drive
Newton Street
Loop 534
Leslie Drive

Figure 3: Example of A Remote Market Near I-10: Kerrville in Texas

trolling or monitoring costs. Thus, franchisors tend to make franchising contracts that do not require high levels of oversight of franchisee. In these markets, most branded hotels and motels are medium quality ones (budget or mid-scale hotels), and tend to have franchising contracts, rather than management contracts. Thus, it is reasonable to assume that franchisees have control over their pricing.

Since this paper uses quarterly data set from 2008 to 2014, a market is defined as an exit-quarter pair, yielding 5,186 hotels in 1,595 markets. In this sample, only 240 hotels can be identified as ones owned by franchisees with multiple hotels. As mentioned earlier, most of these hotels are owned by franchisees associated with multiple franchisors(multi-unit owners). These multi-unit owners exist in 116 of the identified markets.

Market Share To estimate demand parameters, the market share of the outside goods needs to be specified. The most common way of defining outside options is to use demographic information, such as the population of the market (Berry et al., 1995; Nevo, 2000). However, this approach is not reasonable for this paper since most consumers staying at hotels are not residents of local area. Instead, this paper uses unsold rooms in the markets to determine the share of consumers choosing the outside option. Table 1 reports descriptive statistics.[9]

Table 1: Descriptive Statistics of Key Variables

	Mean	SD	Min.	25%.	Median	75%	Max.
Price ($100s)	0.681	0.329	0.134	0.436	0.615	0.857	2.736
Market Shares (Rooms Sold)	0.182	0.152	0.011	0.077	0.135	0.233	0.973
Distance to Exit	0.276	0.112	0.026	0.186	0.282	0.356	0.499
No. of Activities /10	0.267	0.117	0.100	0.200	0.300	0.400	0.500
No. of Room Types /10	0.384	0.141	0.100	0.300	0.400	0.500	0.700
No. of Service for Business /10	0.201	0.087	0.100	0.100	0.200	0.300	0.300
No. of Obs.	5186						
No. of Markets	1595						

1.5.2 Estimation

Following Berry et al. (1995), I estimate the demand parameters defined in Section 4. Similar to Nevo (2000), I include fixed effects of highway exits and hotel chains which accounts for a portion of unobserved product characteristics associated with the markets and hotel chains. To avoid the high dimensional fixed effect issue, the fixed effect absorption approach is used (Correia, 2016; Luoa et al., 2017). To The error term (ξ_{jt}), captures the unobserved product specific deviation from the mean valuation of the unobserved product characteristics. This deviation is assumed to be correlated with prices. To deal with this price endogeneity, this paper uses the nonlinear generalized method of moments (GMM) estimation. Given the initial guess of the unknown parameters, this error term is calculated and then is interacted with a set of the instruments to form the following the population moment condition of the GMM estimation:

---

[9] Details of variables are in the appendix.

$$E[\xi \cdot Z] = 0, \tag{1.11}$$

where Z is a set of instruments which are discussed below. In order to construct the sample moment conditions of the GMM objective function, the mean utility δ is needed. To obtain δ, the contraction mapping approach is used. This approach retrieves δ by equating the estimated market shares with the observed market shares given a value of parameters:

$$s_{jt}^{pred}(x, p_{jt}, \delta_{jt}, \theta_2) = s_{jt}^{obs}, \tag{1.12}$$

where s^{pred} and s^{obs} are the predicted and observed market shares, respectively. Unlike the logit and nested logit models, random coefficient models do not have a closed form solution for δ. Thus, this should be numerically solved, and δ is retrieved by the following the fixed point iterations:

$$\delta_{jt}^{k+1} = \delta_{jt}^{k} + \ln s_{jt}^{obs} - \ln s_{jt}^{pred}(x.p, \delta_{jt}^{k}; \theta_2) \tag{1.13}$$

where δ^k is δ at the kth iteration. Given the initial guess of δ and θ_2, the first iteration starts. In this paper, the criteria for stopping the iteration is $\delta^{k+1} - \delta^k < 10^{-8}$. Given the estimated δ, θ_1 are obtained from the instrumental variable regression.

Once the contraction mapping is completed, δ is estimated. Given this, ξ are obtained:

$$\xi_{jt} = \delta_{jt} - (\alpha p_{jt} + X_{jt}\beta).$$

Once ξ is obtained, θ_2 is estimated by using the following GMM objective function:

$$Q(\theta_2) = \xi(\theta)' Z W^{-1} Z' \xi(\theta), \tag{1.14}$$

where $W = 1/n \sum \xi(\theta_1)\xi(\theta_1)^{-1} Z'Z$ is the weighting matrix. This paper uses the continuously updating weighting matrix, which provides more efficient estimates (Hansen et al., 1996; Baum et al., 2007). The GMM convergence tolerance is 1^{-8}. Since the computation burden is high in the contraction mapping, to speed converge, I use the squared polynomial extrapolation method (SQUAREM)(Reynaerts et al., 2012). SQUAREM speeds up the fixed point iteration and produces more robust convergence results.

I use the optimal instrument approach to obtain efficient demand estimates, especially non-linear ones. Reynaert and Verboven (2014) show how using the optimal instrument approach adds additional moment conditions. Thus, with these additional conditions, the parameter estimates become less biased and more efficient. To do this, I, first, estimate demand parameters without optimal instruments. With these estimates, optimal instruments are formed as the expected Jacobian of the moment condition: $E(D_j(z_t)|z_t)\Phi^{-1}$ where Φ is an identity matrix since the only demand side is considered.[10] Second, I estimate the demand parameters with both these obtained optimal instruments as well as the initial instruments.

Even though the optimal instrument approach is used, one must still find valid instruments to deal with price endogeneity. Valid instruments are correlated with price, but not correlated with unobserved product characteristics. BLP-type instruments (Berry et al., 1995), which are based on the similarity of products are option. Another option are Hausman-type instruments (Hausman, 1996), which capture common components of costs of the same brands across markets. However, these instruments would be inapplicable since a large number of markets have only one or two hotels. In addition, hotel prices are largely determined by local demand and local hotel attributes, rather than common costs under the same brand hotels. Thus, within a brand, variation in prices is high across markets. Instead, I use the approach of Berry and Jia (2010) who use the characteristics of the market as instruments to measure competition when firms face capacity constraints and entry is not exogenous (see route level characteristics in airlines in Berry and Jia's paper). I tested the number of restaurants and gas stations in this paper, but this did not resolve the issue of price endogeneity. Instead, instruments capturing competition and costs are used. To measure competition, the distance to the closest rival within the same exit, and the sum of the rooms of the rivals are used. To measure costs, the number of rooms is used. In addition, interaction terms between the above variables are included if such interactions do not present any collinearity issues.[11]

---

[10] In general cases where demand and supply sides are jointly estimated, optimal instruments are defined as $E(D_j(z_t)\Phi^{-1}|z_t)$, where Φ is a covariance matrix of error terms(ξ, ω).

1.6 Estimated Results

1.6.1 Preliminary Analysis: The effect of Multi-Unit Ownership on Prices

This section includes a descriptive analysis of single- vs. multi-unit owners[12] and a reduced form analysis. This reduced form analysis is preliminary and works as initial support for the structural model approach as well as the following counterfactual analysis. This analysis focuses on only examining the effects of the multi-unit ownership on market prices.

Tables 2 and 3 summarize the characteristics of markets with and without multi-

---

[11] The results of the first stage estimation, which is the regression of price on product charac-

Table 2: Multi-Unit Ownership (All Markets)

Ownership Type	Markets	Hotels
Single-unit (franchisee or independent owner)	1,479	4,946
Multi-unit (with a franchisor or franchisors)	116	240
Total	1,595	5,186

unit ownership. Of 1,595 markets, 116 markets have multi-unit owners (240 hotels).

Table 3: Hotel Characteristics in Markets with Multi-Unit Ownership

		Single-Unit	Multi-Unit
Mean price ($)		81.68	84.62
Standard Deviation of prices		38.33	37.50
No. of Hotels (Units)			
Rating [13]	1	5	3
	2	104	69
	2.5	214	168
	3	32	0
Total		355	240

For the reduced form models, I include fixed effects. To capture these fixed effects, the following indicator variables are included as regressors: 1) multi-unit ownership, 2) same-brand, and 3) same-chain. The value of the dummy variable of multi-unit ownership(Multi-Owner) is one if the hotel owner also own other hotels under a different franchisors, regardless of its brand. Second, if a hotel faces competition from another hotel with the same brand, or under the same franchisors, not owned by the same owners, the value of this dummy variable (Same-Brand) is equal to one. Otherwise it is zero. Third, if a hotel faces competition from hotels within the same hotel chain, the value of this dummy variable (Same-Chain) is

---

teristics (X) and the instruments, are reported in the appendix.

[12] These includes multi-unit franchisees and franchisees with multiple units who are associated with multiple franchisors.

equal to one. Otherwise this is zero.

In addition to these variables, some models include the market concentration index (HHI), the interaction term of HHI and Multi-Owner. These models explore whether concenration in conjection with multi-unit owner is associated with prices. The Herfindahl-Hirschman Index is calculated based on the assumption of multi-unit ownership in markets.[14]

In Table 4, column 1 indicates the reduced form effect of multi-unit ownership on price. The coefficient is significant and positive, indicating that multi-unit owners charge higher prices than single-unit owners.The presence of the same branded (column 2) and of the presence of hotels under the same hotel chain (column 3) have positive effects on prices, but these effects are not significant. This may indicate that in these markets, franchisors, or hotel chains have less impact on prices. Market concentration seems be associated with higher prices, although it is not significant (column 4). The interaction term between HHI and Multi-Owner (column 5) is significant, indicating that multi-unit owners that are in concentrated markets have pronounced effects on prices.

The results of the preliminary regression analysis are only suggestive because multi-unit ownership and multiple hotels under the same brand or the same chain are, for example, likely to be observed in markets with high demand which is, in turn, associated with higher prices. This potential endogeneity concern does not reveal the true effects of multi-unit ownership. The stuctural approach below addresses this shortcoming.

---

[13] Hotel ratings collected from *TripAdvisor* are originally provided by *Expedia*, an online travel agency. See the following website for details of its rating system (https://www.expedia.com/Hotel-Star-Rating-Information).

[14] Assume that both single- and multi-unit owners exist in the markets.

Table 4: Effect of Multi-Unit Ownership (Market Structure) on Prices

	Model				
Dep.Var: Price($100)	(1)	(2)	(3)	(4)	(5)
Multi-Owner	0.091^{***}				
Same-Brand		0.020			
Same-Chain			0.007		
HHI				0.403	0.398
Multi-Owner * HHI					0.278^{***}
Distance to Exit	−0.034	−0.059	−0.062	−0.057	−0.049
No. of Activities	0.790^{***}	0.767^{***}	0.764^{***}	0.766^{***}	0.789^{***}
No. of Room Types	0.231^{***}	0.218^{***}	0.216^{***}	0.219^{***}	0.224^{***}
No. of Service Bus.	1.024^{***}	1.053^{***}	1.060^{***}	1.054^{***}	1.025^{***}
Constant	0.031	0.040	0.041	−0.150	−0.150
Fixed Effects					
Market	Yes	Yes	Yes	Yes	Yes
Observations	5,186	5,186	5,186	5,186	5,186
Adjusted R^2	0.545	0.543	0.543	0.543	0.544

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

1.6.2 Demand Estimates

This section reports demand estimates under the random coefficient model discussed in Section 4 and important estimates obtained from these demand estimates, including price elasticities of demand, marginal costs, and markups.

Table 5 summarizes demand estimation result of the model that uses the optimal instruments. The top panel reports the means of the demand parameters (α, β). The bottom panel shows the standard deviations (σs) of the price variables.[15] These standard deviations capture heterogeneity of consumer preference.

All means of taste parameters (βs) are significant, except the one for the number of room types provided by hotels. All these coefficients have expected signs. Consumers, on average, prefer to stay close to highway exits. As hotels add more

---

[15] Different sets of random coefficients were tested, but the reported and final model are statistically significant and makes economics senses.

Table 5: Results of Demand Estimation

Dep. Var.: $ln(s_j) - ln(s_0)$	Coef. (Std. Err.)
Mean (α, β)	
Price ($100)	-9.982***
	(1.558)
Distance to Exit	-1.193***
	(0.461)
No. of Activities	3.249***
	(0.807)
No. of Room Types	0.738*
	(0.443)
No. of Service for Business	3.469***
	(0.959)
Standard Deviation (σ)	
Price ($100)	3.331***
	(0.847)
Fixed Effects: Location, Chain	
GMM Object Value: 0.000011	

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

amenities and activities, such as bar, restaurant, and pool, consumer utility increases on average. As expected, consumers favor more room type options, while providing amenities targeted at business travelers at hotels— basic office equipment, meeting rooms and conference facilities— increases consumer utility.

The mean price coefficient (α) is statically significant with a negative sign. The standard deviation of this coefficient (σ for α), which is significant, measures the consumer heterogeneity of their willingness to pay for hotel rooms. This helps to obtain more reasonable substitution patterns than those from a simple logit model.

To check the economic plausibility of the demand estimates, I calculate the following estimates: own price elasticities of demand, marginal costs, and markups. Figure 4 shows the distribution of the own-price elasticities (the mean of the own-price elasticities is -4.289 and its standard deviation is 2.081). Even though there are some observations with inelastic demand, these results are by and large reasonable.[16]

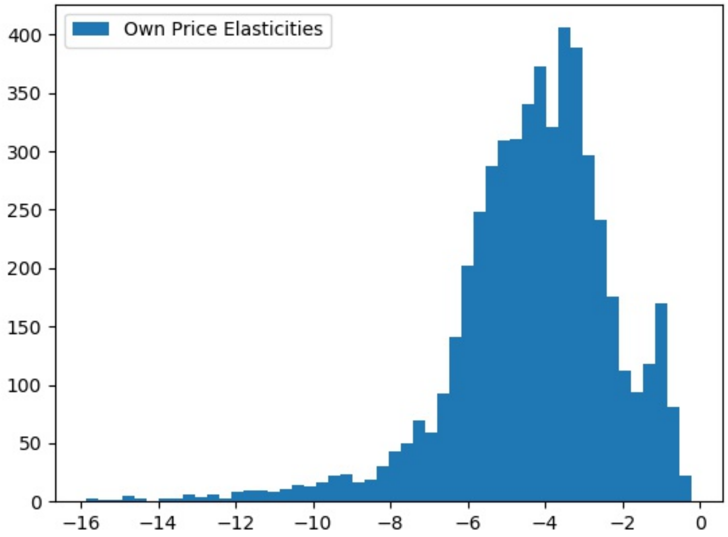

Figure 4: Distribution of Own Price Elasticities

Table 6 and Figures 5 and 6 show, respectively, the descriptive statistics and the distribution of marginal costs and markups. Both marginal costs and markups appear to be within reasonable ranges, thereby validating the demand estimation procedure.

Table 6: Descriptive Statistics of Marginal Costs and Markups

	Mean	Std.	25%	50%	75%
Marginal Costs ($)	50.61	31.41	27.93	44.75	66.23
Markups ($)	17.64	9.67	12.19	14.97	18.86

---

[16] These negative values may result from the existence of highly concentrated markets.

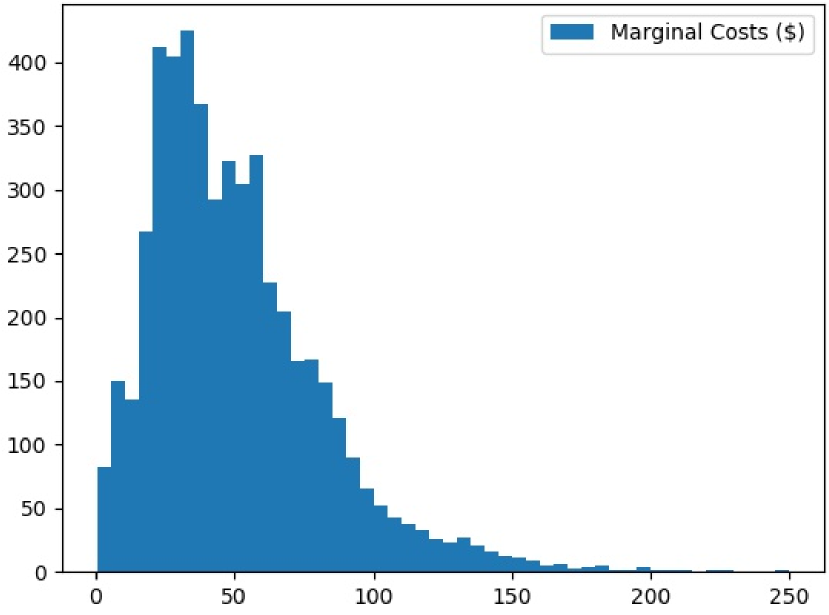

Figure 5: Marginal Costs

1.6.3 Counterfactual Analysis

Changes in Prices, and Market Shares

The purpose of the counterfactual analysis is to examine whether multi-market owners exercise market power. To perform this analysis, I create two different scenarios related to changes in ownership structures: 1) pre-scenario, and 2) post-scenario. The pre-scenario reflects the staus quo (a mix of single- and multi-unit owners), whereas in the post-scenario, all firms are assumed to be single-unit owners. Under the post-scenario, I estimate equilibrium prices by using demand estimates and the assumption given the modified ownership structure.

By comparing the estimated prices under the post-scenario with the observed prices, I empirically measure the market power associated multi-unit ownership. As mentioned earlier, in the baseline counterfactual, I assume that marginal costs,

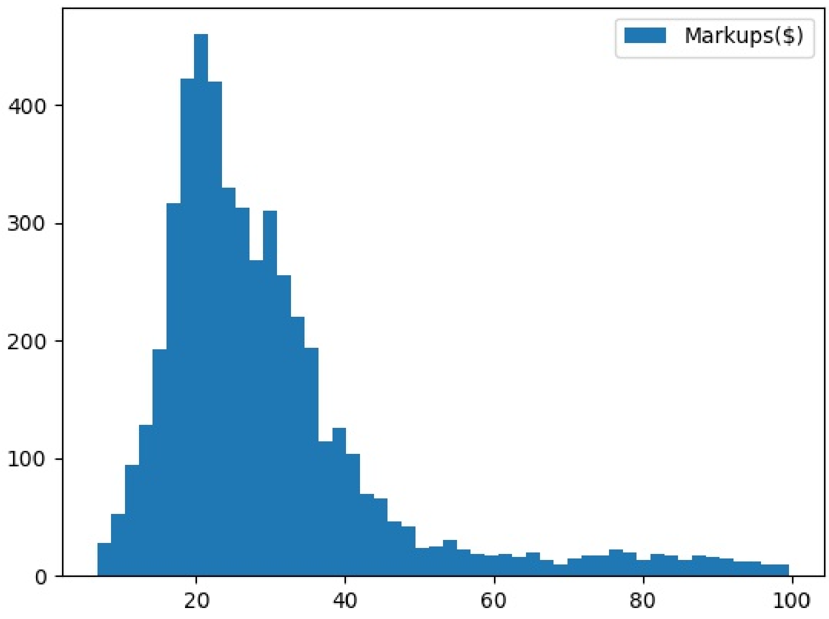

Figure 6: Markups

which are recovered under the pre-scenario, are constant under the post-scenario. Later, I relax this assumption.

Table 7 shows that prices, on average, decrease if all firms were single-unit owners (the post-scenario). The magnitude of the price decrease is higher for multi-unit owners, while single-unit owners do not change significantly. This indicates that multi-unit owners charge higher price because of joint profit maximization, or empirically confirm that they enjoy market power. Due to simulated price reductions, multi-unit owners increase market shares in the counterfactual analysis.

Robust Checks of Price Changes Under Post-Scenario

So far, I have assumed that marginal costs are constant between pre- and post-scenarios. In this section, this assumption is relaxed since multi-unit owners are likely to more efficient than single-unit owners. Some argue that the marginal

Table 7: Changes in Prices and Market Share in Counterfactual Analysis

Variable	Ownership (Pre-Scenario)	Pre[1]	Post [2]	$\frac{\text{Post}-\text{Pre}}{\text{Pre}}$
Price($)	All	82.86	79.62	-3.91%
	Multi	84.62	77.01	-8.99%
	Single	81.68	81.39	-0.36%
Share(%)	All	12.5	13.44	7.52%
	Multi	16.46	20.78	26.25%
	Single	9.82	8.48	-13.65%

1: Both single and multi-unit owners.

2: Single-unit owners

costs that multi-unit owners face are smaller than those of the single-unit owners. Thus, depending ownership structures (single- vs. multi-unit owners), marginal costs would vary. To deal with the assumption on marginal costs related to the types of ownership, I adjust the marginal costs of multi-unit owners that obtained under the pre-scenario when conducting the counterfactual analysis, while marginal costs of single unit owners stay constan. Figure 7 and 8 show how marginal costs vary under the different assumptions. I scale up the recovered marginal costs of multi-unit owners by a series of factors in Table 8. With the new marginal costs, I, then, estimate equilibrium prices under the post-scenario. The marginal costs obtained under the pre-scenario are used as a benchmark for single- and multi-unit owners. For the single-unit owners, marginal costs are constant under both the pre- and post-scenarios. However, marginal costs of the multi-unit owners under the post-scenario are likely higher than those obtained under the pre-scenario. I use a series of the percentage increases (5% to 10%) of marginal costs of the multi-unit owners (the benchmark costs of the multi-unit owners). Details of the setup of the counterfactual analysis are summarized in Table 8:

With these newly adjusted marginal costs, corresponding equilibrium prices are obtained. The results of this additional counterfactual analysis are summarized in

Table 8: Additional Counterfactual Analysis with Different MC

	Pre		Post		Estimate Price
Model	Single-Unit	Multi-Unit	Single-Unit	Multi-Unit	(p_c^*)
Baseline	$\hat{mc}$	$\hat{mc}$	$\hat{mc}$	$\hat{mc}$	p^*
Model 1	$\hat{mc}$	$\hat{mc}$	$\hat{mc}$	$\hat{mc}$ * 1.05	p_1^*
Model 2	$\hat{mc}$	$\hat{mc}$	$\hat{mc}$	$\hat{mc}$ * 1.06	p_2^*
Model 3	$\hat{mc}$	$\hat{mc}$	$\hat{mc}$	$\hat{mc}$ * 1.07	p_3^*
Model 4	$\hat{mc}$	$\hat{mc}$	$\hat{mc}$	$\hat{mc}$ * 1.08	p_4^*
Model 5	$\hat{mc}$	$\hat{mc}$	$\hat{mc}$	$\hat{mc}$ * 1.09	p_5^*
Model 6	$\hat{mc}$	$\hat{mc}$	$\hat{mc}$	$\hat{mc}$ * 1.1	p_6^*

Table 1.1 and Figure 8. As the marginal costs that are used in the counterfactual analysis increase, prices $(p_1*, \cdots, p_6^*$ with respect to (p^*). However, the estimated price (p_c^*) remains below than the observed prices (p), indicating that prices would decrease without the multi-unit owners in the markets, even after considering that converting multi-unit owners to single-unit ones may increase their marginal costs by up to 10%.

Table 1.1: Changes in Prices($p*$) with Different Marginal Costs

Ownership	p	p^*	p_1^*	p_2^*	p_3^*	p_4^*	p_5^*	p_6^*
All	82.865	79.621	80.9	81.162	81.426	81.692	81.96	82.23
(%)	0.00%	-3.91%	-2.37%	-2.06%	-1.74%	-1.42%	-1.09%	-0.77%
Multi	84.623	77.012	79.911	80.502	81.097	81.695	82.298	82.905
(%)	0.00%	-8.99%	-5.57%	-4.87%	-4.17%	-3.46%	-2.75%	-2.03%
Single	81.677	81.386	81.568	81.607	81.648	81.689	81.731	81.773
(%)	0.00%	-0.36%	-0.13%	-0.09%	-0.04%	0.01%	0.07%	0.12%

p: the observed prices, p^*, p_c^*: estimated prices; %: Percentage changes (%) from the observed prices

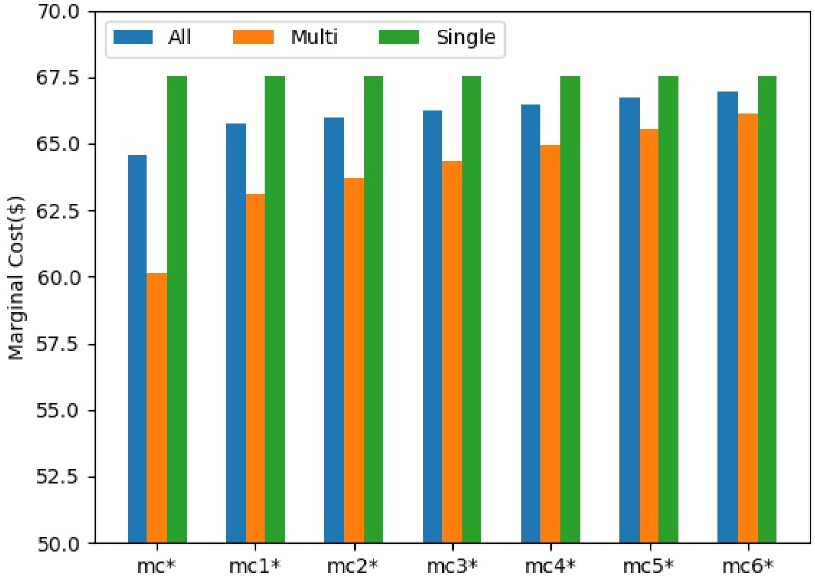

Figure 7: Various Marginal Cost Assumptions

In sum, market power seems to be a likely explanation (vis-á-vis efficiency) for the increase in price that one observes in multi-unit operation.

Consumer Welfare

To measure changes in consumer welfare, I calculate the market-level compensating variation(CV). Total annual CV for all markets is \$ 43,998,262.12, which is equivalent to 5.22% of total consumer annual spending. Thus, without multi-unit ownership, consumers would spend 4% less than what they actually do, holding their utility constant. This results from the decreased prices under the counterfactual scenario, increasing consumers' mean utilities higher, resulting in positive CV.

Figure 9 shows how average compensating variations at markets change depend-

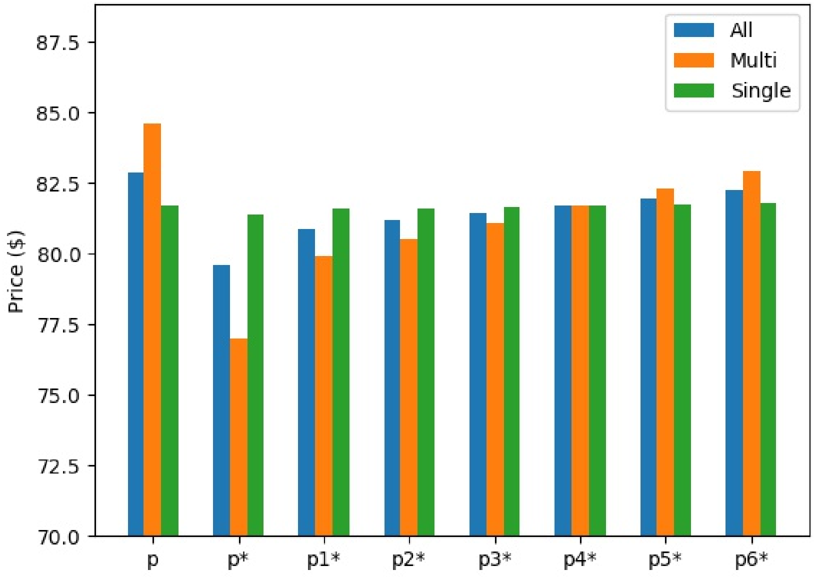

Figure 8: Price Variations

ing on the assumption on marginal costs (Section 1.6.3).[17] As estimated marginal costs increase for multi-unit owners, the average compensating variations decreases accordingly, indicating that consumer welfare decreases, but consumers would be better off without multi-unit ownership.

1.7 Conclusion

This paper investigates the effects of multi-unit ownership on prices, market shares, and consumer welfare by analyzing data on hotels near interstate highway exits in Texas to answer the following question: Why do franchisees have multiple units that are associated with more than one franchisor? Using data of prices, quantities, ownership, and hotel characteristics, I identify hotels owned by multi-

---

[17] CV^* represents CV calculated with price p^*. All other CVs are calculated with corresponding estimated prices. For example, CV_1^* is obtained with price p_1^*.

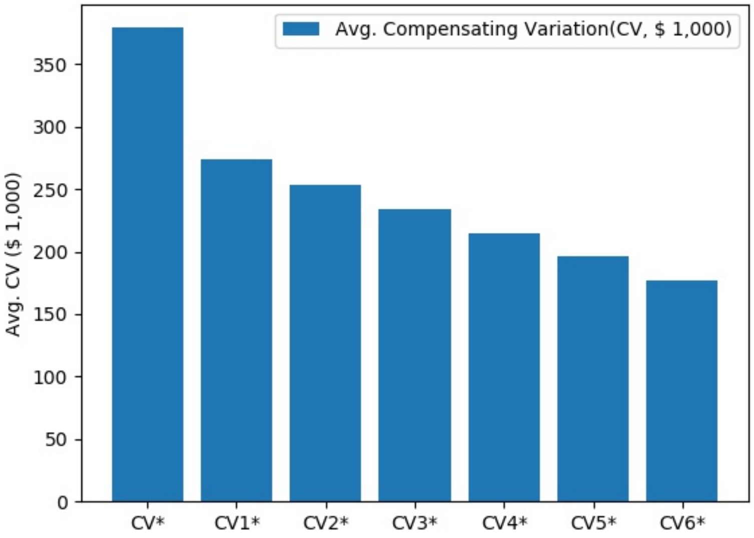

Figure 9: Changes in Average CVs with Different Marginal Costs

unit owners in narrowly defined, geographical markets. Given the sample and the market definition, I conduct reduced-form model analysis and find evidence suggesting that multi-unit ownership and multi-unit franchising are associated with higher prices.

Motivated by the results of the reduced-form analysis, I estimate demand parameters using a random coefficient logit model. With the estimated parameters, I conduct a counterfactual analysis to analyze how firms would have charged prices in the absence of multi-unit ownership(the post-scenario). I measure the market power of multi-unit owners by comparing observed prices in the markets with estimated prices under the post scenario. The results support the hypothesis that multi-unit owners exercise market power: in the post scenario, prices, on average, decrease by 4.1 %, with the price decreases being larger for multi-unit owners (8.47%). This result is consistent with additional counterfactual analyses under the different assumptions of marginal costs. The market shares of all owners increase by approximately 7.2%, on average, while most increases in market of the multi-unit owners are larger (26.06%). Finally, welfare analysis indicates that under under the counterfactual scenario, consumers would increase welfare with the respect to the multi-unit ownership status quo.

The findings of this paper provide a unique view on franchising, especially the role of franchisees. Franchisees have been considered as downstream firms in the vertical relationship between both vertical separation (i.e., two independent firms at each vertical level) and vertical integration(i.e., an integrated firm controlling both vertical levels). In the examples of the current paper where franchisors may have limited power and resources of control over franchisees, franchisees can act as vertically separated firms within the vertical relationship. Using the lodging industry as an example, this paper finds that some franchisees have multiple franchising contracts with more than one franchisors, which result in higher prices. With multi-unit ownership, these owners can conduct joint-profit maximization when their units are in the same market. This evidence provides one explanation for why owners might want to operate multiple units in local markets and why franchisors would have an incentive to permit this.

Some limitations need to be considered when interpreting the results of this study. First, the narrow market definition in this paper might exclude some markets with multi-unit owners. Similar to markets near interstate highway exits, multi-unit owners may exist in cities, especially metropolitan areas. If these large markets were included, it is not certain whether I would be able to obtain reliable substitution patterns across firms in a market, which is crucial for counterfactual analysis. It is also impossible to exclude the cross-market competition across neighbor markets. Second, multi-unit owners might operate units in different markets in which the owners exercise market power through different mechanisms, such as multi-market contact. Even though this is beyond the scope of this paper, it would be interesting to analyze other operational/management decisions by multi-unit owners.

CHAPTER 2

MULTIMARKET CONTACT, PRICING, AND FRANCHISING: A STUDY OF THE HOTEL INDUSTRY IN TEXAS

2.1 Introduction

Multimarket contact (MMC) is frequently observed in retail and service industries: competitors face the same rivals in different geographic markets. The concurrent nature of competition that emerges in these cases can create incentives that are conducive to supra-competitive prices. Bernheim and Whinston (1990) show that competition of firms with multiple contacts in a repeated game setting can give rise to collusive equilibria. Since Bernheim and Whinston (1990), several empirical studies have confirmed this theoretical prediction in various industries: airline (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 the empirical literature on the effects of MMC in two dimensions. First, we take into account the extent of vertical control that is often observed in these retail industries. While the hotel industry is often characterized by a vertical separated structure, an important degree of vertical control is exercised by the upstream firms via franchising contracts with the downstream units. Importantly, some degree of vertical control is necessary for the MMC collusive equilibria to emerge: if the downstream firm is fully independent from the upstream unit, then there is little reason for the downstream to internalize or consider the pricing behavior of hotels outside its market. On the other hand, if the upstream firm has partial control of downstream operations across multiple franchisors, in particular as it pertains to pricing, then theoretical incentives for collusion become relevant. Intuitively, a firm may start a price war in one market in retaliation to a rival firm's reluctance to adhere to a collusive price in another market.

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

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

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

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

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

---

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

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

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

The paper is organized as follows. Section 2.2 reviews related work. The data are described in Section 2.3. Reduced form and structural models are presented in Section 2.4. Section 2.5 presents the results. Section 2.6 concludes and discusses possible extensions for future research.

2.2 Literature Review

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

$$\pi_j^m(R_j(p_k^m), p_k^m) + \frac{\delta}{1-\delta} v_j^m \leq \frac{1}{1-\delta} \pi_j^m(p_j^m, p_k^m), \forall j \neq k \tag{2.1}$$

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 2.1 represents the payoff from deviation, while the right hand side is the payoff from cooperation.

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

$$\sum_m \pi_j^m(R_j(p_k^m), p_k^m) + \frac{\delta}{1-\delta} v_j^m \leq \sum_m (\frac{1}{1-\delta} \pi_j^m(p_j^m, p_k^m)) \tag{2.2}$$

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

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

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

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

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

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

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

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

Williams, 2014).[3]

In other cases, however, it is less clear whether an ad-hoc geographic market definition is reasonable. For instance, Jans and Rosenbaum (1997) use metropolitan cities with a 200 mile-limit as a market definition for the cement industry. Feinberg (2014) adapt similar strategies to define markets for movie theaters (mid-size metropolitan cities). Fernandez and Marin (1998) and Silva (2015) use government defined tourism or business districts to delineate geographic markets for hotels in Spain. In these cases, the resulting geographic markets are large; a consequent drawback of such market definitions is that the degree of MMC would be significantly underestimated. For example, it is reasonable to assume that a hotel on the outskirts of a large city (e.g. near the airport) does not compete head to head with a hotel located in the business downtown area; however, a broad market definition that includes all hotels in the city could consider these hotels as being in the same geographic market.[4]

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

---

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

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

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

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

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

2.3 Data

2.3.1 Data Source

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

---

[5] See Appendix A for details of this review

Prices, quantities, capacity (the number of rooms), and brand affiliation are retrieved from *Source Strategies INC*. Hotel characteristics, such as facilities, amenities, and services, are collected from *TripAdvisor*.

2.3.2 Market Definition: Clustering Approach

Clustering algorithms, a non-parametric tool, groups observations into mutually exclusive sets such that observations in a cluster are more closely related to each other than they are to observations in other clusters. Although various clustering algorithms are available, we use a density-based spatial cluster algorithm with noise (DBSCAN) (Ester et al., 1996). We use this algorithm since DBSCAN is more data-driven approach without prior assumptions on data. This algorithm does not require a pre-determined number of clusters. Unlike other clustering algorithms, such as the K-mean clustering and hierarchical clustering, DBSCAN can form clusters with little knowledge of markets. Further, the algorithm does not rely on other ex-ante (arbitrary) assumptions such as the number of clusters.[6]

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

---

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

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

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

To set a reasonable distance limit, one can use information on the distribution of pair-wise distances between hotels. For instance, a distance limit can be set to a level where a reasonable fraction of pair-wise distances are captured. To do this, we focus on the pairwise (Euclidean) distances between each hotel and its four nearest competitors [8]. Using this set of distances, we select each hotel's distance to the fourth most distant competitor and visualize its cumulative distribution (Figure 10).

As the distance increases, more hotels have their 4th nearest competitor within such distance. Based on Figure 10), we use 0.04 as the distance limit (approximately 1.5 miles), as this value captures the large majority of pair-wise distances (94.05%).

The results of the clustering are summarized in Figure 11. The algorithm produces 21 clusters, with 359 observations for four quarters (Around 90 observations per quarter) considered as noise points (and excluded from the reduced form and

---

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

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

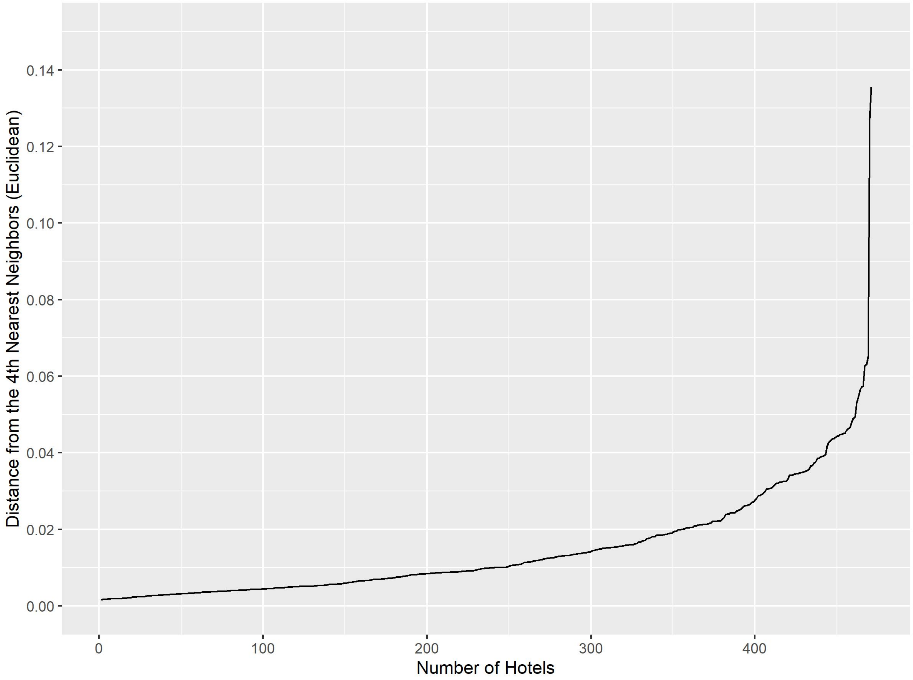

Figure 10: Distribution of Distance from the Fourth Nearest Neighbor (2014 Q1)

structural models analyses).

2.3.3 Measures of Multimarket Contact

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

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

---

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

Pair-Specific Measure of MMC

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

$$MMC_{jk}^{m} = \frac{\sum_{m' \neq m} I_j^{m'} \cdot I_k^{m'}}{\sum_{m'} I_j^{m'}} \tag{2.3}$$

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

Firm-Specific (Aggregate) Measure of MMC

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

$$AMMC_j^m = \sum_{k \neq j}^{F^m} MMC_{jk}^m. \tag{2.4}$$

We note that none of the independent hotels in our data operate units across markets. As a consequence, independent hotels have measures of MMC (MMC_{jk}, and $AMMC_j$) equal to zero. Independent hotels, however, are included when defining markets and in the estimation of the reduced form model and in the structural analysis. Further, consistent with prior literature (Fernandez and Marin,

---

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

1998; Silva, 2015), we define firms (i.e. j, k) at the brand level (e.g., Four Points, Courtyard), rather than at the chain level (i.e., Marriott).

2.3.4 Descriptive Statistics

Table 9 displays descriptive statistics. The top panel shows the main variables whereas the bottom panel shows the MMC measures.

As mentioned earlier, the MMC for independent hotels is equal to zero. Thus, the table separately reports the MMC measure for the subset of branded hotels. Figure 12 shows the distribution of MMC_{jk} for branded hotels.

Table 9: Descriptive Statistics of Key Variables

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

1: Noise observations are dropped though DBSCAN.

2: HHI represents the capacity-based Herfindahl index.

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

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

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

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

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

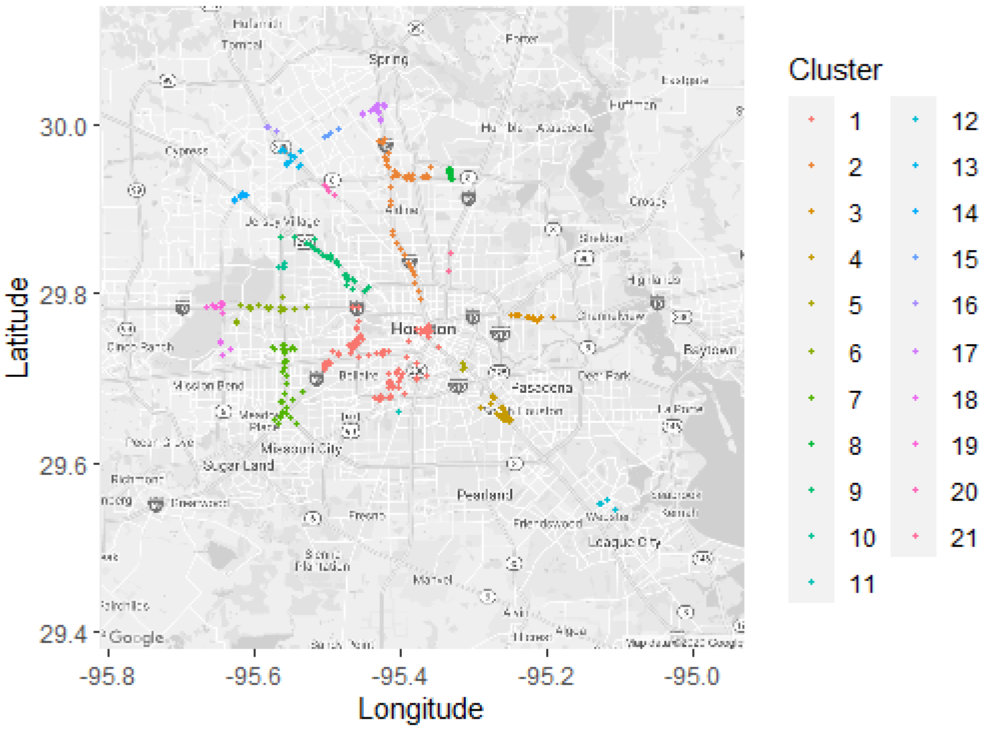
Cluster
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
Latitude
30.0
29.8
29.6
29.4
Longitude
-95.8
-95.6
-95.4
-95.2
-95.0
Tomball
Spring
Cypress
Humble
Jersey Village
Aldine
Crosby
Sheldon
Channelview
Houston
Baytown
Bellaire
Pasadena
Deer Park
Mission Bend
Cinco Ranch
Missouri City
Sugar Land
Pearland
Friendswood
League City
Fresno
Manvel
Google

Figure 11: Clusters of Houston, TX (2014 Q1)

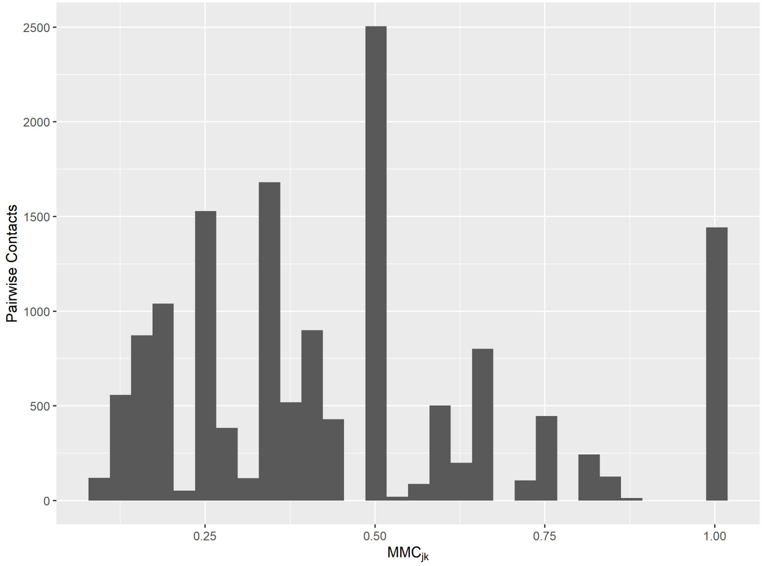

Figure 12: Distribution of MMC_{jk} for Branded Hotels

2.4 Model and Estimation Details

2.4.1 Reduced Form Model

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

$$P_j^{mt} = \alpha_1 AMMC_j^{mt} + \beta X_j^{mt} + \nu_j^{mt} \tag{2.5}$$

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

2.4.2 Structural Model

Demand Side

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

$$\begin{aligned} u_{ij}^m &= \alpha p_j^m + X_j^m \beta + \xi_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij}^m \\ &= \delta_j^m + \zeta_{ig} + (1-\sigma)\epsilon_{ij}^m \qquad (2.6) \end{aligned}$$

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

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

$$s_j = s_{jg} \cdot s_g \qquad (2.7)$$

$$s_{jg} = \frac{\exp(\frac{\delta_j}{1-\sigma})}{\sum_{j \in F_g} \exp(\frac{\delta_j}{1-\sigma})} = \exp(\frac{\delta_j}{1-\sigma})/D_g \qquad (2.8)$$

$$s_g = \frac{D_g^{(1-\sigma)}}{\sum_g D_g^{(1-\sigma)}} \qquad (2.9)$$

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

---

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

$$s_j = s_{jg} \cdot s_g = \frac{\exp(\frac{\delta_j}{1-\sigma})}{D_g^{\sigma}[\sum_{g'} D_{g'}^{(1-\sigma)}]} \tag{2.10}$$

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

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

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

$$\ln(s_j) - \ln(s_0) = \alpha p_j + X_j\beta + \sigma \ln(s_{jg}) + \xi_j \tag{2.11}$$

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

$$g(\theta^d) = E[Z_d\xi]. \tag{2.12}$$

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

Supply Side

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

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

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

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

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

---

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

$$\begin{aligned}\pi_f^m = & \underbrace{(p_j^m - mc_j^m)s_j^m M^m}_{\text{Own (Single-Unit) Profits}} \\ & + \underbrace{\sum_{j' \in F_f} f_{vc}(I_{jj'}; \lambda_{vc})(p_{j'}^m - mc_{j'}^m)s_{j'}^m M_m}_{\text{Consideration of Vertical Control}} \\ & + \underbrace{\sum_{k \neq j, j'} f_{mmc}(MMC_{jk}; \lambda_{mmc})(p_k^m - mc_k^m)s_k^m M_m}_{\text{Consideration of MMC}} \end{aligned} \tag{2.13}$$

where mc_j^m is product j's marginal costs in market m, and M^m represents the market size of market m'. $I_{jj'}$ is an indicator variable that is equal to 1 if firms j and j' belong to franchisor f. $f_{vc}(I_{jj'}; \lambda_{vc})$ is a function with parameter λ_{vc} that maps $I_{jj'}$ onto the $[0, 1]$ interval while $f_{mmc}(MMC_{jk}; \lambda_{mmc})$ is a function with parameter λ_{mmc} that maps MMC_{jk} (as described earlier) onto the unit interval.

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

Equation 2.13 for market m can be written in matrix form as follows:

$$\Pi^m = \Lambda^m(P^m - MC^m)S^m M^m. \tag{2.14}$$

To illustrate how the three models we consider are mathematically represented in Equation 2.14, consider an example in which there are three hotels, and hotels 1 and 2 belong to the same franchisor; hotel 3 belongs to a separate franchisor. Then, matrix Λ for each model is presented as follows:

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

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

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

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

The first order condition of the profit function (Equation 2.13) is:

$$\begin{aligned} & s_j^m + (p_j^m - mc_j^m)\frac{\partial s_j^m}{\partial p_j^m} \\ & \quad + \sum_{j'}(p_{j'}^m - mc_{j'}^m)\frac{\partial s_{j'}^m}{\partial p_j^m} f_{vc}(I_{jj'\in F_f}) \\ & \quad + \sum_{k}(p_k^m - mc_k^m)\frac{\partial s_k^m}{\partial p_j^m} f_{mmc}(MMC_{jk}) = 0 \end{aligned} \tag{2.15}$$

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

$$mc^m(\lambda_{vc}, \lambda_{mmc}) = p^m - \Omega^{-1}(\lambda_{vc}, \lambda_{mmc}) \cdot s^m(\hat{\alpha}, \hat{\beta}) \tag{2.16}$$

where $\Omega = -\Lambda \cdot \partial s/\partial p$, where $\partial s/\partial p$ is a matrix of derivatives with entry k, j equal to $\frac{\partial s_k^m}{\partial p_j^m}$). In Equation 2.16 all components are known (prices and shares are observed, and partial derivatives come from demand estimation), except for the conduct parameters. To estimate conduct parameters, we use a GMM approach similar to the one used on the demand side. Specifically, marginal cost for product j in market m is defined as a linear function of cost:

$$mc_j^m = W_j^m \rho + \omega_j^m \tag{2.17}$$

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

Using Equations 2.16 and 2.17, marginal cost shocks are rewritten as follows:

$$\omega_j^m = p_j^m - W_j^m \hat{\rho} - \Omega^{-1}(\lambda_{vc}, \lambda_{mmc}) \cdot \hat{s}_j^m(\hat{\alpha}, \hat{\beta}). \tag{2.18}$$

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

$$g(\theta_s) = E(Z_s \omega) = 0 \tag{2.19}$$

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

Identification To estimate the conduct parameters in Equation 2.19, it is crucial to use a set of instruments that can separately identify markups from unobserved marginal cost shocks. As discussed in Michel and Weiergraeber (2018), valid instruments should be correlated with the endogenous variables (the conduct parameters), while being exogenous to random cost shocks. We use two sets of variables satisfying these two conditions: 1) the numbers of hotels under the same hotel brand in the market and in the city (i.e., how many hotels are operated by a hotel brand) and 2) the numbers of hotels under the hotel chain with which the firm's brand is associated in the market and in the city (i.e., how many hotels of a different brand are operated by the hotel chain with which the hotel is associated).

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

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

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

---

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

Additional Details To mitigate misspecification and ease computational burden, demand and supply sides are estimated separately. To estimate the conduct parameters in Equation 2.13, we use the following specifications:

$$f_{vc}(I_{jj'};\lambda_v) = \frac{exp(\lambda_v)}{1+exp(\lambda_v)} I_{jj'} \tag{2.20}$$

$$f_{mmc}(MMC_{jk};\lambda_{mmc}) = \frac{exp(\lambda_{mmc})}{1+exp(\lambda_{mmc})} MMC_{jk}. \tag{2.21}$$

These specifications restrict the estimated conduct parameters to be on the unit interval ($0 \leq f_{vc} \leq 1; 0 \leq f_{mmc} \leq 1$), as required by economic theory: an off-diagonal element in Λ (see Equation 2.14) equal to one for f_{vc} denotes full vertical control (zero denotes independence of the franchisee with respect to the franchisor) while an entry of one for f_{mmc} denotes perfect collusion through MMC (zero indicates that MMC is irrelevant for pricing decisions).

2.5 Results

2.5.1 Reduced Form Models

Table 10 reports a battery of OLS results. The first three specifications include non-brand fixed effects: an indicator variable whose value is one if hotels are non-branded. The last three specifications include chain fixed effects. [14] All

---

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

Table 10: Results of Reduced Form Model

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

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

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

2.5.2 Structural Models

Demand Side

Demand estimates from our preferred specification are summarized in Table 11. All coefficients have the expected sign. Consumers dislike paying high prices and derive a higher utility from more activities (restaurants, pools, bars, meeting facilities, etc.) and services (concierge, shuttle bus, etc.). On average, hotels in downtown Houston are preferred than those near the George Bush Intercontinental Airport.

Table 11: Results of Demand Estimation

Dep. Var.: $\ln(s_j)$ - $\ln(s_0)$	Coef. (Std.Err)
Price	-0.054^{***}
	(0.004)
No. of Activities	0.344^{***}
	(0.053)
No. of Serivice	0.194^{***}
	(0.043)
Downtown	3.537^{***}
	(0.380)
Airpot	-1.082^{***}
	(0.301)
$\ln(s_{jg})$	0.441^{***}
	(0.092)
Constant	2.055^{***}
	(0.355)
Fixed Effects:	
Quarter	Yes
GMM Objective Values	0.1416

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

The chain fixed effects that were included in Table 10 are not included in 11 since these fixed effects may be correlated with other variables, such as the number of activities and the number of services. It is likely that hotel chains or hotel brands keeps the same set of activities or services across their hotels.

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

Supply Side

Table 12 summarizes the estimates of the supply side for the three models we consider. Consistent with expectations, results indicate that the marginal cost of providing a hotel room increases with the number of room amenities and the number of services. Also, larger hotels exhibit greater marginal costs. While this may seem counterintuitive (i.e. there are no economies of scale), we note that larger hotels usually have higher ratings; one would, thus, expect higher-quality hotels to have larger marginal costs.

Table 12: Results of Supply Side Estimation

Dep. Var.: 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

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

Turning to the coefficient on multi-market contact, the results from models 2 and

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

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

We use the estimates from Table 12 to compute the conduct parameters vertical control and MMC conduct parameters as per Equations 2.20 and 2.21. Table 13 reports the results. The effect of MMC on prices is 74% larger in model 3 than in model 2 (0.9588 v. 0.5499). Further, model 3 supports the notion that vertical control in the hotel industry exists, but it is only partial. A key takeaway from these results is that models that either neglect vertical control or impose it are likely to produce structural estimates that are biased.

Table 13: Estimated Conduct Parameters

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

Counterfactual Analysis

To quantify the effect of MMC on prices and, we conduct a counterfactual analysis in which the effect of MMC in models 2 and 3 is turned off. Table 14 summarizes how conduct parameters are set up under the counterfactual scenarios.

Table 14: Set Up For Conduct Parameters for Counterfactual Analysis

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

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

$$p^* = mc + \Omega^{-1}(p^*)s(\hat{\alpha}, \hat{\beta}, p^*) \tag{2.22}$$

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

Table 15: Comparison of Average Observed Prices and Equilibrium Prices

	Observed	Model 2		Model 3	
	p	p_2^*	% Change	p_3^*	% 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_m*: the estimated average price of model m
% Change: the percentage changes from p

The results of counterfactual analysis are summarized in Table 15. Removing the effect of MMC would decrease prices by approximately 1.4% in model 2 and by 1.54% in model 3. Quantitatively, the effect is in line with what has been reported in prior studies (e.g., Molnar et al., 2013; Khwaja and Shim, 2017). Since MMC

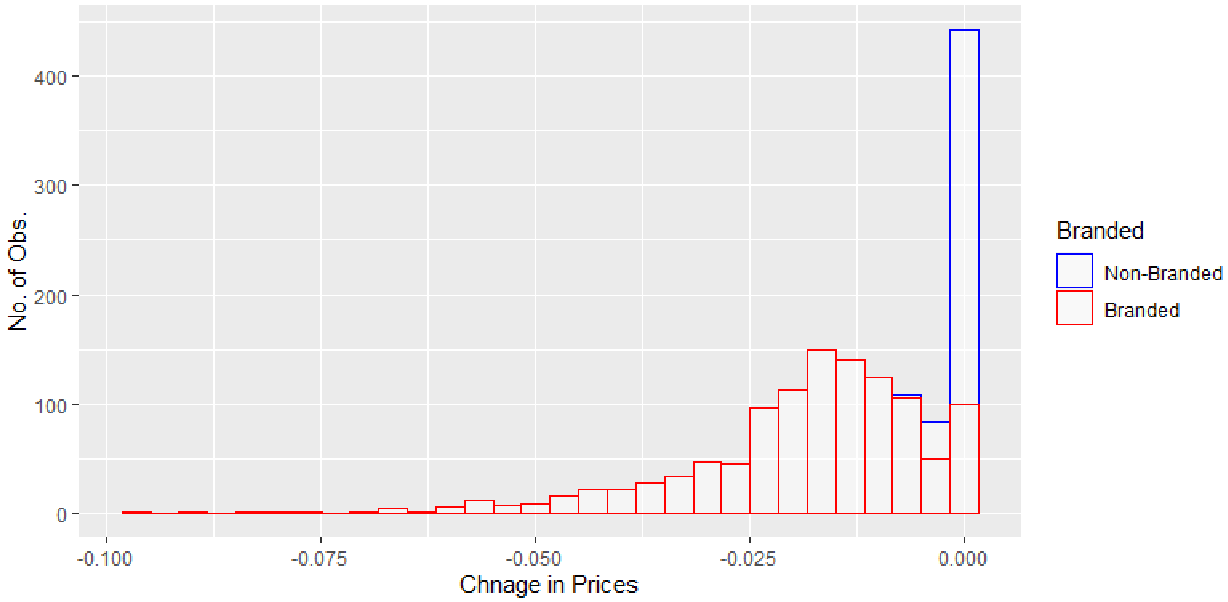

Figure 13: Changes in Price Under Model 2

occurs only for branded hotels, the effect on non-branded hotels is minimal (see Figures 13 and 14). As expected, since MMC has a greater effect on prices in model 3, removal of MMC in model 3 results in a larger (albeit moderately so) price decrease than in model 2.

2.6 Conclusion

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

This paper contributes to the literature in two ways. First, we employ a data-driven approach to define geographic markets in an area where no prior distinct markets would be identifiable. The approach exploits spatial agglomeration pat-

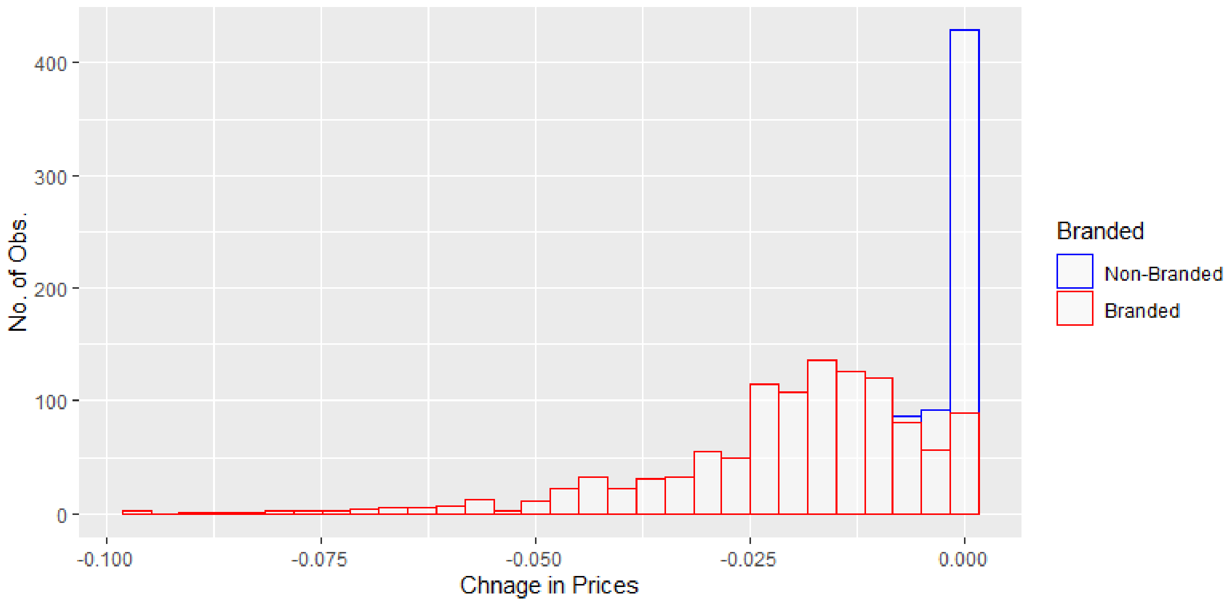

Figure 14: Change in Prices Under Model 3

terns to identify the most likely hotel clusters of competition in the Houston metropolitan area. The defined markets are then used to carry out structural and counterfactual analyses. While our application focuses on a specific industry and area of the country, the approach can be implemented in other industries or geographic areas.

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

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

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

APPENDIX A

Appendix for Chapter 1

A.1 Multi-Unit Owners in Texas

Table 16: Multi-Unit Owners in Different Market Definitions

(Unit: Hotel)

Market Definition		Period	Total	MUO Hotels[0]	Avg. MUO Hotels
State[1]	All		18,050	2,494 (13.8%)	623.50
	MSA	4[5]	14,318	2,165 (15.1%)	541.25
	Non-MSA		3,732	245 (6.6%)	61.25
City[2]	All		18,050	1,391 (7.7%)	347.75
	MSA	4[5]	14,318	1,266 (8.8%)	316.50
	Non-MSA		3,732	125 (3.3%)	31.25
Highway[3]		28[6]	5,186	240 (4.6%)	8.57

0: Hotels owned by multi-unit owners

1: State as a single market

2: Cities as markets

3: The definition of market in this paper

4: 4 periods (2014Q1 to 2014Q4

5: 28 periods (2008Q1 to 2014Q4)

Table 17: Market Size by Market Types

Type	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
All	1,595	3.251	2.297	1	2	4	12
Single & Multi[1]	116	5.129	2.656	2	3	9	10
Single[2]	1,479	3.104	2.200	1	2	4	12

1: Markets with both single- and multi-unit owners

2: Markets with only single-unit owners

Table 18: Descriptive Statistics by Ownership Types in All Markets

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Price							
All	5,186	68.101	32.930	13.379	43.589	85.742	273.621
Multi[1]	240	84.623	37.503	22.800	60.006	98.645	223.530
Single[2]	4,946	67.300	32.483	13.379	43.017	85.227	273.621
Room							
All	5,186	62.594	26.910	9	46	74	200
Multi[1]	240	67.046	23.854	24	52	97	105
Single[2]	4,946	62.378	27.033	9	45	74	200
Rating							
All	5,186	2.125	0.536	1	2	2.5	3
Multi[1]	240	2.337	0.272	1	2.	2.5	2.5
Single[2]	4,946	2.115	0.544	1	2	2.5	3

1:Multi-Unit Owners, 2:Single-Unit Owners

Table 19: Descriptive Statistics of Owners in Markets with Multi-Unit Owners

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Price							
All	595	82.865	37.994	22.800	58.066	96.403	223.530
Multi[1]	240	84.623	37.503	22.800	60.006	98.645	223.530
Single[2]	355	81.677	38.330	26.518	55.420	94.766	210.890
Room							
All	595	73.613	35.609	24	52	96	200
Multi[1]	240	67.046	23.854	24	52	97	105
Single[2]	355	78.054	41.165	25	55	96	200
Rating							
All	595	2.361	0.312	1	2	2.5	3
Multi[1]	240	2.337	0.272	1	2.	2.5	2.5
Single[2]	355	2.377	0.336	1	2	2.5	3

1:Multi-Unit Owners, 2:Single-Unit Owners

A.2 Variable Definitions

Table 20: Variable Descriptions

Variables	Description
Prices of hotels (p_{jt})	Average Daily Room Rate (\$100)
Distance to Exit	Distance to the nearest highway exits (Miles)
Shares of hotels	Rooms sold / total rooms available in the market
No. of Activities	Restaurant, bar, lounge, pool, gym, spa, and kid-activities
No. of Room Types	No. of Room types available in hotels
No. of Services for Bus.	Meeting room, conference facility, business center, and fax/office support.

A.3 Results of the First Stage Regression

Table 21: Results of First Stage Regression

Dep. Var.: Price	Coef. (Std.Err.)
Exogeneous Var.	
Distance to Exit	-0.099^{***}
	(0.036)
No. of Activities	0.361^{***}
	(0.044)
No. of Room Types	0.090^{***}
	(0.034)
No. of Services Bus	0.367^{***}
	(0.061)
Instruments	
Distance to Rival	-0.031^{*}
	(0.018)
No. of Rooms	-0.110^{***}
	(0.016)
Sum of Rivals' Rooms	0.056^{***}
	(0.005)
No. of Rooms * Distance to Rival	0.002
	(0.028)
Sum of Rivals' Rooms * Distance to Rival	0.010^{*}
	(0.005)
Fixed Effect:	Location, Chain
Observations	5,186
Adjusted R^2	0.641
F Statistic	129.654^{***}

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

APPENDIX B

Appendix for Chapter 2

B.1 Analysis of Franchise Disclosure Documents

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

Even though the sample of this study is hotels in Houston, Texas, using FDDs fromn the state of Wisconsin is still a pertinent for two reasons. First, most franchisors use uniform franchise contracts for their franchisees (in some cases across countries). Second, the state of Texas does not require filing of FDDs. [1]

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

---

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

Revenue management systems and consulting services may facilitate franchisors' control over prices at franchised units. The primary focus of these revenue management systems is to choose the right prices to maximize revenues given market conditions and inventories/demand of individual hotels.[2] To achieve this, the revenue management system collects data, makes forecasts for demand and inventories, and recommend prices for various consumer groups. The systems do not force franchisees to choose specific prices, but can inform them of their suggested prices. Table B.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 or chains. For example, Red Lion Hotels' *Revenue Management Insight* provides basic market reports covering regional competitors and their pricing. Wyndham has various levels of the consulting services (Platinum, Gold and Diamond) with a mandatory service for opening hotels. These consulting services include basic market reports, and marketing/pricing strategies.

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

---

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

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

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

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

---

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

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

Table B.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 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	G6ROW Rate Administration(Required), G6ROW Revenue Optimization(Optional)

Continued from the previous page (Table B.1)

Chain	Brand	Name & Optional(Required)
	Studio 6	
Hilton	Doubletree Embassy Hampton Hilton Garden Hilton Home 2 Homewood	QnQ (Required), Revenue Management Consolidated Center(Optional, but required for some cases)
Hyatt	Hyatt House Hyatt Place Hyatt Regency	Hyatt central system (Required), Revenue Optimization Service(Option, but required for Hyatt Regency
IHG	Candlewood Holiday Inn Indigo InterContinental Staybridge Crowne Plaza	IHG Concerto(Required), Yield & Price Optimization(Required), Revenue Management for Hire Service(Optional, but required for some cases)
La Quinta	La Quinta	Revenue Management Services
Marriott	Aloft Courtyard Element Le Merrian Marriot	Revenue Management Advisory Services, Cluster Revenue Management (Both optional, but required for some cases)

Continued from the previous page (Table B.1)		
Chain	Brand	Name & Optional(Required)
	Sheraton Springhill Westin Fairfield Four Points	
Radison	Country Inn Park Inn Radison	Revenue Optimization Program (Optional)
Red Lion	Best Value Inn Guest House Knights Inn	IDeas G3(Required), Revenue Management Insight (Optional)
Wyndham	Day Inn Hawthon Howard Microtel Ramada Super 8 Travelodge Wingate Wyndham Garden Wyndham Baymont	Central Rate and Inventory Support Program(Required), Short Term Revenue Management Services(RMS) (Required), Platinum, Gold, and Diamond RMS (Optional)

Continued from the previous page (Table B.1)

Chain	Brand	Name & Optional(Required)

B.2 Robustness Check of Market Definition: Distance Metric Approach

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

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

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

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:

$$p_j = R(p_{-j}) = \sum \beta x_j^m + g(d_{jk})p_k + \epsilon_j \tag{B.2}$$

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:

$$P = R(P') = X\beta + GP' + \epsilon \tag{B.3}$$

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

$$P = X\beta + \gamma W P + \epsilon, \tag{B.4}$$

where

$$G = \gamma W = \gamma \frac{1}{n} \begin{bmatrix} 0 & 1/d_{12} & \cdots & 1/d_{1n} \\ 1/d_{21} & 0 & \cdots & 1/d_{2n} \\ \vdots & \cdots & \ddots & \vdots \\ 1/d_{n1} & \cdots & 1/d_{nn-1} & 0 \end{bmatrix} \tag{B.5}$$

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

$$\hat{\beta}_{jk} = \hat{\gamma} \frac{1}{d_{jk}} \tag{B.6}$$

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

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

Table 22: Price Reaction Function Estimation

Dep. Var.: Price	Coef. (Std. Err.)
WP (γ)	0.016***
	(0.002)
Rating	14.611***
	(0.267)
No. of Room	0.059***
	(0.004)
HI Sales	21.025***
	(1.927)
Constant	46.245***
	(3.62)
Fixed Effects	
Quarter	Yes
Observations	1,880
R^2	0.308
Adjusted R^2	0.306

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Figure 15 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.

B.2.1 An Issue with the Distance Metric Approach

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

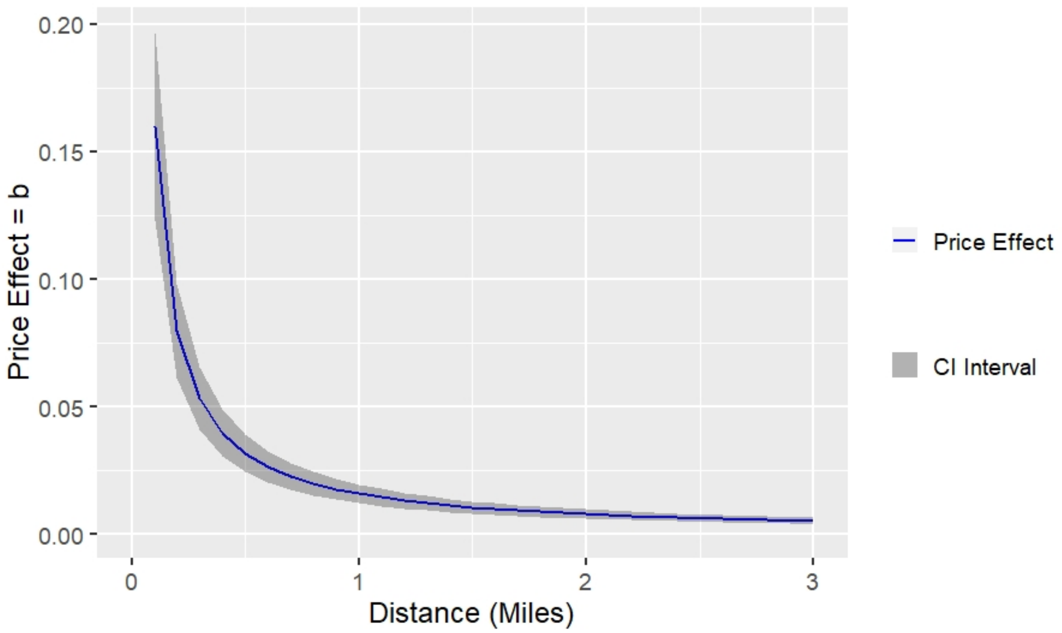

Figure 15: Price Effects (Changes in Distance)

demonstrates this issue:

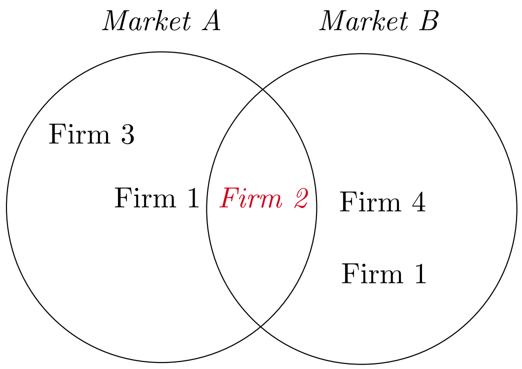

Figure 16: Double Counting

In Figure 16, the left circle represents the market of firm 1; the right circle, the market for firm 4. Texts in the figure represent the location of each firm. Firm 2 belongs to both firm 1's market (the left circle) and firm 4's market(the right circle). Thus, since firm 1 exists in the right circle, firm 2 can be a rival for firm 1 in the right circle. At the same time, firm 2 can be a rival for firm 1 in the left circle.

The second issue is indirect effects. Figure 17 illustrates the indirect effects of a rival that has no direct contact with a firm. The market of firm 4 includes firm 5 that may affect firm 1's behavior through their direct rival, firm 2. This effect may not be negligible since in the hotel industry, a firm's behavior is highly affected by its local rivals.

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

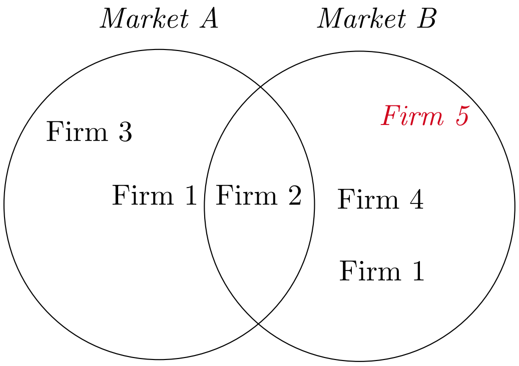

Figure 17: Indirect Effects

B.2.2 Firm Specific Measures of MMC

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

$$AVMMC_j^m = \frac{\sum_{k \neq j}^{F^m} \sum_{m' \neq m} I_j^{m'} \cdot I_k^{m'}}{N^m - 1} \tag{B.7}$$

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

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

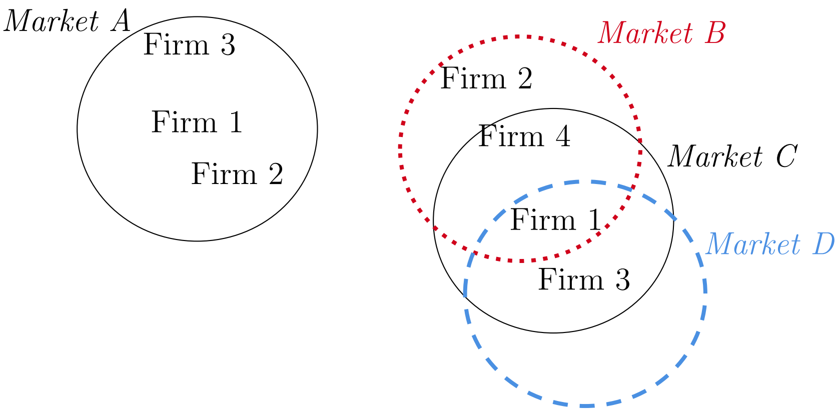

Figure 18: How to Calculate AVMMC

The method of calculating $VMMC$ is the same in both measures, while these measures are different in recognizing other markets given a focal market.

AVMMC AVMMC considers all possible markets created by the distance metric approach if the firms are sufficiently distant from a focal firm. Figure 18 graphically explains how to calculate AVMMC under the distance band approach. Markets are created by the distance metric approach. Assume that one calculates the multimarket contacts of firm 1 in the left circle. In this approach to AVMMC, this paper assumes the distance bands of all firms to be independent markets. This means firm 1 appears in the three right circles in Figure 18: Markets B (Firm 4's market), C (Firm 1's second market), and D (Firm 3's market). Thus, there are three other markets. In market B, firm 1 has contact with firm 2, while firm 1 has contact with firm 3 in markets C and D. Thus, the average multimarket contacts for firm 1 in market A are $3/2 = 1.5$ (total number of contacts of rivals in other markets (B,C, and D) / No. of rivals in the focal market (A), AVMMC=1.5).

AVMMC2 Since AVMMC may face issues of double counting in other markets, to circumvent this issues, an alternative counting approach, AVMMC2, is used. In this counting approach, we only consider markets that a firm is a focal firm. For example, when calculating $AVMMC2_i^m$ for firm i in market m, only markets where firm i is the focal firm are considered. Figure 19 graphically explains how to caculate $VMMC2$. Assume we are interested in the $AVMMC2$ of firm 1 in market A. Rather than considering two markets B and D in $AVMMC$, market C (firm 1's second focal market) is treated only as another market for firm 1 in market A. Thus, $AVMMC2$ of firm 1 in market A is 0.5 since firm 1 has a contact only with firm 3 in market C ($AVMMC2 = 0.5$). Thus, with this approach, we can avoid this double-counting issue, especially when firms locate in close geographic areas.

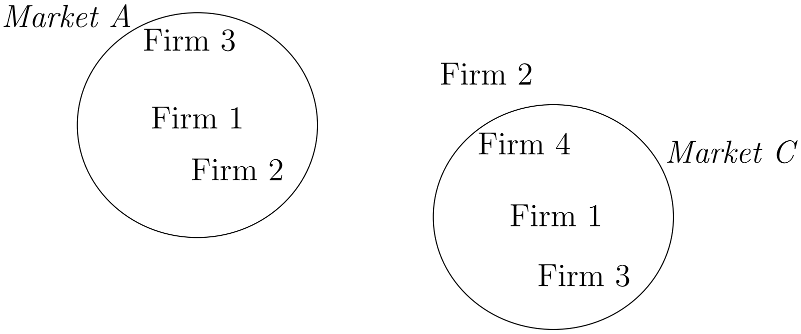

Figure 19: How to Calculate AVMMC2

B.2.3 Descriptive Statistics of Key Variable Under the Distance Metric Approach

Table 23: Descriptive Statistics of Key Variables

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

B.2.4 Results of Reduced Form Models

The reduced form models used with these market definitions are similar to the one used in this paper. Tables 24 summarizes the estimation results of the reduced form models with fixed effects. The results from both tables support the view that hotels with more MMC tend to charge higher prices. This means that MMC facilitates collusive behaviors, consistent with prior studies of MMC in the hotel industry (Fernandez and Marin, 1998; Silva, 2015).

Depending on the measures of MMC, the magnitudes of the coefficients of MMC vary, but economic relevance of the effects of MMC is consistent. Thus, we use the standard deviation of the measures of MMC to interpret the meaning of the coefficients of MMC. In Table 24, one standard deviation increase in AVMMC raises prices by $\$2.577 = 0.088 \times 29.279$. Similarly, one standard deviation increase in AVMMC2 makes prices higher by $\$3.719 = 2.788 \times 1.334$. Both cases show similar increased prices due to one standard deviation increases in the measures of MMC.

Table 24: Estimation Under Distance Metric Approach

	Model	
Dep. Var.: Price	(1)	(2)
AVMMC	0.088^{***}	
	(0.029)	
AVMMC2		2.788^{***}
		(0.622)
Rating	28.679^{***}	28.799^{***}
	(0.580)	(0.579)
HHI	-29.174^{***}	-31.318^{***}
	(6.679)	(6.666)
Constant	25.308^{***}	23.842^{***}
	(2.282)	(2.255)
Fixed Effects		
Chain	Yes	Yes
Observations	1,274	1,274
R^2	0.665	0.667
Adjusted R^2	0.664	0.667

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

BIBLIOGRAPHY

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

Baum, C. F., Schaffer, M. E., Stillman, S., et al. (2007). Enhanced routines for instrumental variables/gmm estimation and testing. *Stata Journal*, 7(4):465–506.

Bernheim, B. D. and Whinston, M. D. (1990). Multimarket contact and collusive behavior. *RAND Journal of Economics*, 21(1):1–26.

Berry, S. and Jia, P. (2010). Tracing the woes: An empirical analysis of the airline industry. *American Economic Journal: Microeconomics*, 2(3):1–43.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, 63(4):841–890.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *RAND Journal of Economics*, 25(2):242–262.

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

Blair, R. D. and Lafontaine, F. (2005). *The Economics of Franchising.* Cambridge University Press.

Brunner, D., Heiss, F., Romahn, A., Weiser, C., et al. (2017). Reliable estimation of random coefficient logit demand models. Technical report, University of Düsseldorf, Düsseldorf Institute for Competition Economics (DICE).

Chaudey, M. and Fadairo, M. (2008). Contractual design as a determinant of performance: Evidence from franchising. *International Journal of the Economics of Business*, 15(1):117–127.

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

Correia, S. (2016). Linear models with high-dimensional fixed effects: An efficient and feasible estimator.

Dahlstrom, R. and Nygaard, A. (1999). An empirical investigation of ex post transaction costs in franchised distribution channels. *Journal of Marketing Research*, 36(2):160–170.

Davis, P. (2006a). Measuring the business stealing, cannibalization and market expansion effects of entry in the us motion picture exhibition market. *Journal of Industrial Economics*, 54(3):293–321.

Davis, P. (2006b). Spatial competition in retail markets: movie theaters. *Rand Journal of Economics*, 37(4):964–982.

Ester, M., Kriegel, H.-P., Sander, J., and Xu, X. (1996). A density-based algorithm for discovering clusters in large spatial databases with noise. In *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining*, KDD'96, page 226–231. AAAI Press.

Evans, W. N. and Kessides, I. N. (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 Marin, P. L. (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 Jeong, E. (2001). Multimarket contact: Meaning and measurement at multiple levels of analysis. In *Multiunit organization and multimarket strategy*, pages 357–408. Emerald Group Publishing Limited.

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

Hansen, L. P., Heaton, J., and Yaron, A. (1996). Finite-sample properties of some alternative gmm estimators. *Journal of Business & Economic Statistics*, 14(3):262–280.

Hausman, J. A. (1996). Valuation of new goods under perfect and imperfect competition. In *The economics of new goods*, pages 207–248. University of Chicago Press.

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

Jans, I. and Rosenbaum, D. I. (1997). Multimarket contact and pricing: Evidence from the us cement industry. *International Journal of Industrial Organization*, 15(3):391–412.

Kalnins, A. (2004a). Divisional multimarket contact within and between multiunit organizations. *Academy of Management Journal*, 47(1):117–128.

Kalnins, A. (2004b). 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):203–203.

Kalnins, A. and Lafontaine, F. (2004). Multi-unit ownership in franchising: evidence from the fast-food industry in texas. *RAND Journal of Economics*, 35(4):747–761.

Kalnins, A. and Mayer, K. J. (2004). Franchising, ownership, and experience: A study of pizza restaurant survival. *Management Science*, 50(12):1716–1728.

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

Kidwell, R. E., Nygaard, A., and Silkoset, R. (2007). Antecedents and effects of free riding in the franchisor–franchisee relationship. *Journal of Business Venturing*, 22(4):522–544.

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

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

Lafontaine, F. (1992). Agency theory and franchising: some empirical results. *RAND Journal of Economics*, 23(2):263–283.

Luoa, S., Zhub, W., and Ellisa, R. P. (2017). An iterative approach to estimation with multiple high-dimensional fixed effects. Technical report, Working paper.

Mazzeo, M. J. (2002a). Competitive outcomes in product-differentiated oligopoly. *Review of Economics and Statistics*, 84(4):716–728.

Mazzeo, M. J. (2002b). Product choice and oligopoly market structure. *RAND Journal of Economics*, 33(2):221–242.

Mazzeo, M. J. (2004). Retail contracting and organizational form: Alternatives to chain affiliation in the motel industry. *Journal of Economics & Management Strategy*, 13(4):599–615.

McFadden, D. (1989). A method of simulated moments for estimation of discrete response models without numerical integration. *Econometrica*, 57(5):995–1026.

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

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

Nevo, A. (2000). Mergers with differentiated products: The case of the ready-to-eat cereal industry. *Rand Journal of Economics*, 31(3):395–421.

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

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

Reynaert, M. and Verboven, F. (2014). Improving the performance of random coefficients demand models: the role of optimal instruments. *Journal of Econometrics*, 179(1):83–98.

Reynaerts, J., Varadhan, R., Nash, J. C., et al. (2012). Enhancing the convergence properties of the blp (1995) contraction mapping. Technical report, KU Leuven, Faculty of Economics and Business, VIVES Research Centre for Regional Economics.

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

Schmalensee, R. (1978). Entry deterrence in the ready-to-eat breakfast cereal industry. *Bell Journal of Economics*, 9(2):305–327.

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

Thomadsen, R. (2005). The effect of ownership structure on prices in geographically differentiated industries. *RAND Journal of Economics*, 36(4):908–929.

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

Waldfogel, J. and Wulf, J. (2006). Measuring the effect of multimarket contact on competition: Evidence from mergers following radio broadcast ownership deregulation. *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).