The Effect of Franchising on Store Performance and Consumer Utility

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ABSTRACT

JEFFREY ACKERMANN: The Effect of Franchising
on Store Performance and Consumer Utility
(Under the direction of Brian McManus)

I estimate the effect that franchising a store has on its performance. There is a substantial literature predicting that a franchisee-owned store will generate higher profits than a franchisor-owned store, all else equal. However, attempts to estimate the effect of franchising on store performance are hampered by an important selection issue: the franchisor may choose to assign the least desirable locations to franchisees. I overcome this issue by using a 2007 corporate sale that resulted in all franchisor-owned Applebee's stores in Texas being sold to franchisees as a source of exogenous variation. While I do not observe store profits, Texas makes store-level alcohol sales data available for all bars and restaurants that have a liquor license; I use alcohol revenues as a proxy for store performance.

In the first chapter, I provide a review of relevant literature, create a model of a profit-maximizing franchisor to illustrate the identification challenge that I face, and give an overview of my data. In the second chapter, I first find evidence that both observable and unobservable location-level factors were important in Applebee's decision to own or franchise a store prior to the corporate sale. I then use a linear model with store level fixed effects to estimate the effect of franchising on store performance. In the third chapter, I create a structural model that uses consumer and store locations to predict alcohol sales for all bars and restaurants with a liquor license in Texas. Using this model, I find that franchising an Applebee's store increases its alcohol revenues by seven percent. I also find that franchising a store produces a consumer utility gain comparable to a 2.8-mile reduction in distance from the individual's home to the store.

For Lauren and Madeline and Claire, whose unconditional love has brought me unspeakable joy.

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CHAPTER 1

BACKGROUND

My dissertation work examines the impact of franchising on firms and consumers. The research is unique because it identifies a selection problem and then uses a unique identification strategy to solve the problem and provide an estimate of the effect of franchising on firm performance. While a substantial body of research has been done regarding the reasons that firms choose to franchise some or all of their stores, little work has been done on how franchising affects a store's performance. Attempts to estimate the effect of franchising on store performance have been hampered by an important selection issue: the franchisor selects the ownership of each store and can therefore choose the ownership configuration that maximizes franchisor profits. This may lead to the franchisor owning stores in the most desirable locations while franchisees are assigned the less lucrative locations. Thus, it is important to determine if differences in store performance between company-owned and franchisee-owned stores are due to differences in ownership or differences in location quality. I use a novel data source and a unique source of identification to identify the effect of franchising on store performance.

In the first chapter, I begin with a review of relevant literature. I then create a simple model of a franchisor's decision process regarding whether a given store should be company-owned or franchised. I then use this model to show why an estimation of the effect of franchising that does not account for unobservable differences in location quality may lead to biased estimates. I show that a 2007 corporate acquisition that resulted in a large number of company-owned Applebee's restaurants being sold to franchisees provides the identification necessary in order to measure the effect of franchising. The chapter ends with a discussion of the data used in this dissertation: restaurant-level alcohol tax revenues in the state of Texas.

In the second chapter, I first present evidence that, prior to the corporate sale, both observable and unobservable location level factors were important in Applebee's decision to own or franchise a store. I then use a linear model with store level fixed effects to estimate the effect of franchising on store performance. I find that franchising a store has a positive impact on revenue, and I find that failing to account for unobservable differences in location quality would have resulted in the effect of franchising being underestimated.

In the third chapter, I create a structural demand model which uses consumer and store locations to predict alcohol sales for all bars and restaurants in Texas with a liquor license over a ten year period. I find that franchising an Applebee's restaurant increases its revenue by about 7 percent and provides substantial utility gains to consumers.

1.1 Review of Literature

Interfirm relationships account for approximately half of all economic activity in the United States and are the subject of a substantial amount of theoretical and empirical work. Included in this research is an extensive literature discussing the tradeoffs between vertical integration and vertical separation. In this section, I first provide an overview of literature that discusses the role moral hazard plays in interfirm relationships. I then provide a longer discussion of literature that specifically discusses franchising as an organizational form. Lastly, I discuss research that uses empirical models of spatial competition.

1.1.1 Interfirm Relationships and Moral Hazard

Moral hazard has frequently been used to help explain the nature of interfirm relationships. Here I discuss research on interfirm relationships that is especially relevant for my work.

Anderson and Schmittlein (1984) provide an empirical analysis of the principal-agent problem that occurs between firms and workers. They use a logit analysis to predict when firms will choose to use an outside firm, rather than employees, to sell their products.[1] Grossman and Hart (1986) generate a theoretical model that considers both principal (upstream) and agent (downstream) moral hazard when assessing the tradeoffs associated with vertical integration.

Holmstrom and Milgrom (1994) create a model that looks at various methods, which the authors list as “high-performance incentives, worker ownership of assets, and worker freedom from direct controls”, for motivating workers. The authors are especially interested in why many relationships between firms and employees or contractors include aspects of all three methods. This is important in the context of franchising, because these methods are all exhibited in the franchising relationship. The authors find that each method can be successfully used to mitigate worker moral hazard, and that the methods are often compliments.

Slade (1998) examines a vertical relationship known as “traditional franchising.” Traditional franchising occurs when a franchisor manufactures a product and sells it to the franchisee, who resells the product to customers. Traditional franchising is substantially different from business format franchising, which is the subject of my dissertation. Her model indicates that, when it is difficult to monitor franchisee effort or when high retail prices charged by one franchisee may hurt the brand’s reputation, it is advantageous for the franchisor to choose the price charged by franchisees. She then tests these predictions using an empirical analysis of the relationship between oil companies (franchisors) and affiliated service stations (franchisees) in Vancouver.[2] Using price and sales data, she finds evidence supporting her predictions. She also finds that, when pricing decisions are delegated to the retailer, prices tend to be higher.

[1] Lafontaine (1992), Sen (1993), and Scott (1995) each use a similar empirical analysis to investigate the motivations for franchising.

[2] Fuel retailing is one industry in which traditional franchising is very common. Other industries where this is the case include car dealerships and soft drink bottlers; see Slade (1996) and Arruñada et al. (2001) for further discussion of traditional franchising.

Several papers look at the economics of sharecropping. Sharecropping has many similarities to franchising. Like franchising, a downstream firm (the tenant farmer) pays the upstream firm (the land owner) for the rights to use the assets of the upstream firm, and a portion of the farmer's payment is a form of revenue sharing. Stiglitz (1974) was among the first to analyze two possible reasons for the sharecropping relationship to exist. The first is risk sharing. He notes that farming is an inherently risky venture and contrasts two organizational forms that would result in one party assuming all of the risk: in one scenario, the farmer would be paid a fixed salary, leading to all risk being borne by the franchisor, while in another scenario, the farmer would rent the land at a fixed fee from the landowner, leading to all risk being borne by the farmer. Sharecropping, on the other hand, allows both parties to assume some risk, because franchisee payments are lower during low-yield years and greater during high-yield years. The second reason he gives for the existence of sharecropping is monitoring difficulties; specifically, if the landowner is unable to monitor farmer effort, a purely wage-based compensation method will result in shirking by the farmer. Stiglitz also explores the interactions between risk aversion and monitoring difficulties. While the optimal contract from a monitoring difficulty perspective is one in which the farmer rents the land at a fixed fee (and, therefore, bears the full cost of shirking), risk averse farmers will tend to have some revenue sharing in their contracts.

Ackerberg and Botticini (2002) examine agreements between land owners and tenant farmers in early Renaissance Italy. They explore the importance of unobserved heterogeneity among agents in contract selection. They find that, when there are unobserved differences in the preferences of land owners or farmers, empirical methods which use observable characteristics of agents to predict contract choice can produce misleading results. After controlling for these differences, the authors find evidence that revenue sharing was used to share risk between the two parties.

1.1.2 Franchising

I now look closer at one specific type of interfirm relationship: franchising. Franchising is an organizational form in which a franchisor creates a product, business plan, and trademarks and then sells the right to open a branded store to a franchisee. The contract typically contains both a fixed fee and a variable component that depends on store performance. Thus, the franchisor acts as the upstream firm while the franchisee acts as the downstream firm.

Two early papers analyzing interfirm relationships that looked specifically at franchising are Rubin (1978) and Klein (1980). Rubin criticizes what was, at the time, the most common theory of why franchising exists: capital-constrained franchisors. This theory suggests that franchising allows a capital-constrained firm to expand more quickly than it could if it were required to pay all costs associated with opening new stores. He argues that, if franchising primarily existed as a method for franchisors to gain access to capital, then franchisors would work to minimize franchisee risk so as to minimize the risk premium that would need to be paid to a risk averse franchisee. Rubin suggests that this could be accomplished by giving each franchisee a share of profits from all franchised outlets. Instead, franchisees tend to have relatively high-risk portfolios: exclusive ownership of a small number of geographically concentrated stores. Rubin suggests that minimizing franchisee moral hazard is the most important reason why firms use franchising. He uses some anecdotal evidence on store ownership, which makes this one of the first franchising papers with an empirical component. Klein addresses the topic of seemingly "unfair" interfirm contracts and, as an example, notes that franchise contracts often appear to be one-sided because the franchisor demands a substantial initial investment while reserving the right to terminate the contract for a variety of reasons. He then suggests that the structure of franchise contracts is designed to minimize franchisee cheating, where "cheating" is defined as free-riding on the franchisor's brand and producing a low-quality product.

Mathewson and Winter (1985) develop some theoretical foundations for the economics of franchise contracts. They find that the potential for franchisee free riding is a necessary condition for franchising to be an optimal strategy. They also predict that franchisors will execute some degree of control over franchisees, such as imposing quality standards and business practice standards.

Brickley and Dark (1987) empirically examine chains that have both franchisor-owned and franchisee-owned stores. They find that stores in locations with high monitoring costs are more likely to be franchised; this is evidence that franchising is used to solve a moral hazard problem. They also find that chains where stores are likely to serve the same customers repeatedly tend to franchise a larger share of their stores; this supports the hypothesis that franchisees free-riding on the franchisor's brand is an important concern. Specifically, a franchisee who rarely serves repeat customers will be tempted to serve a low-quality product, because the negative impact of the diminished brand reputation will be borne largely by other stores. Interestingly, while a common prediction in theoretical literature is that a store located at a highway exit will be less likely to serve repeat customers and therefore less likely to be franchised,[3] Brickley and Dark find no such relationship.[4] They theorize that a store's proximity to a highway exit is not a good predictor of its likelihood of serving repeat customers.

Minkler (1990) introduces what he describes as a "search cost" reason for franchising. He explains that if franchisees "possess superior knowledge about local markets, they can more cheaply search for the best inputs, production processes, and marketing strategies..." I refer to this as the "local expert" theory throughout my dissertation. He then tests this hypothesis using data on locations, opening dates, and franchise status for Taco Bell stores located in California and Nevada. He finds some limited evidence supporting his theory.

[3] Rubin (1978) and Mathewson and Winter (1985) both make this prediction.

[4] Minkler (1990) also finds no evidence that stores near a highway are less likely to be franchised.

Lafontaine (1992) uses data on 548 franchisors with 150,000 total affiliated stores to test various theories related to franchising. She finds that chains that operate in more states (which she uses as a proxy for geographic dispersion) and chains that require more discretion on the part of the store's manager are more likely to use franchising; this supports the hypothesis that monitoring difficulties and franchisee moral hazard are important considerations for a franchisor. She also finds that when franchisor inputs are important to store success, royalty rates are higher and more stores are company-owned. Both factors increase the franchisor's incentive to maximize systemwide sales; thus, the results support the hypothesis that franchisor moral hazard is a significant determinant of franchising behavior. Lafontaine also observes that, for a given franchisor, each franchisee has the same fee structure. Sen (1993) uses a data set similar to that of Lafontaine and conducts similar analyses. Like Lafontaine, he finds evidence that moral hazard for both the franchisee and franchisor plays an important role in the franchising relationship. He also finds evidence that the startup investment required for a store is positively correlated with the fixed franchise fee and that a franchisor's brand name recognition is positively correlated with its royalty rate. He finds no evidence that franchisee risk aversion is an important factor in the franchising relationship. Lafontaine and Sen both find that capital market imperfections are not an important predictor of franchising behavior.

Kaufmann and Lafontaine (1994) seek to explain why anecdotal evidence suggests that McDonald's franchisees frequently earn positive rents, even though basic franchising theory predicts that a franchisor can design franchise fees such that the ex ante expected value of store profits go to the franchisor.[5] The authors first use financial data to confirm that franchisees do, in fact, earn positive ex ante rents. They then offer predictions of why McDonald's allows its franchisees to earn positive economic profits. They note that McDonald's has a strong preference for franchisees who do not hold another job and are

[5]The authors distinguish between ex ante and ex post rents. Specifically, they explain that ex post rents may exist as a means to encourage franchisees to give their full effort.

closely involved in the day-to-day operations of the store, as opposed to investor groups who may take a more hands-off approach to franchise ownership. The authors theorize that this leads to franchisees with lower wealth levels and less liquidity, and that these liquidity constraints prevent McDonald's from charging a higher initial franchise fee.

Mathewson and Winter (1994) consider the choice made by franchisors of whether to grant exclusive territories to franchisees. They construct a theoretical model which indicates that granting exclusivity to franchisees is profit maximizing when franchisee inputs are especially important to store success. This is because exclusive territories encourage franchisee investments by ensuring that the franchisee's future profits will not be harmed by the opening of a nearby store affiliated with the same chain. They find empirical evidence that chains whose franchisees are entrusted with more decisions (as measured by the franchisees' discretion over advertising and prices) are more likely to grant exclusive territories, supporting their hypothesis.

Schmidt (1994) uses a linear city framework to model competition between franchisees affiliated with the same franchisor. He finds that, in the absence of a royalty rate, competition between franchisees will result in prices that are below the price that would maximize system-wide profits. A positive royalty rate serves to increase prices to the optimal level by increasing marginal costs for the franchisees. This result is somewhat counterintuitive, because royalty rates are typically thought to result in inefficient outcomes due to the fact that the marginal cost faced by the franchisee is not the true marginal cost of production and, as a result, prices are above what would be charged by a profit-maximizing vertically integrated firm. He uses the empirical results of Lafontaine (1992) and Sen (1993), which find that franchisors with more outlets (which he considers a proxy for the degree of intra-franchise competition) tend to charge higher royalty rates, as evidence supporting his theory.

Scott (1995) focuses on franchisor moral hazard. He considers the possibility that franchisees, having made substantial firm-specific investments, are subject to opportunistic behavior by a franchisor. For example, a franchisor could fail to make expenditures that are necessary to maintain brand reputation. He hypothesizes that franchisors use franchisor-owned stores to incentivize themselves to maintain the brand's reputation, thus encouraging potential franchisees to trust the franchisor's commitment to maintaining brand reputation. Scott then conducts an empirical analysis similar to that used by Lafontaine (1992). He uses a different data set and different proxies from Lafontaine for the importance of franchisor effort, but obtains similar results: when franchisor effort is more important, chains tend to have a higher share of franchisor-owned stores.

Bhattacharyya and Lafontaine (1995) investigate a contracting feature common in franchising: the tendency of revenue-sharing contracts to use simple, linear rules which are not customized for each individual contract.[6] They develop a model that looks at the optimal way to write a revenue sharing or profit sharing contract when both parties are tempted to exert sub-optimal effort (double-sided moral hazard). They first find that, with some general assumptions, it can be shown that the optimal revenue sharing rule can be implemented with a linear contract. They also find that, in many cases, the optimal royalty rate does not depend on market size or franchisee characteristics. However, they do not attempt to explain why the fixed franchise fee tends to be the same for all franchisees.

Lutz (1995) focuses on asset ownership in franchising, specifically that franchisees own many local assets, but franchisors own trademarks and other assets. She asserts that, while franchising is considered to be used primarily to mitigate moral hazard issues by properly incentivizing the manager, a properly designed incentive plan could accomplish the same goals without franchising; specifically, the manager of a company-owned store could have her pay more closely tied to the store's performance. She then suggests that asset ownership is a crucial component of franchising and that, because both the

[6] In the case of franchising, this means that franchisees pay a fixed share of their revenue to the franchisor and that this share does not vary over time.

franchisee and franchisor own brand-specific assets, both are motivated to maximize chain profits. Furthermore, she finds that franchising may be a profit-maximizing arrangement even if employee managers are as productive as franchisees.

Lafontaine (1995) and Graddy (1997) both compare the prices charged at company-owned and franchisee-owned fast food restaurants. Both find that franchisee-owned establishments charge higher prices. Lafontaine gives two possible reasons for this finding. The first is a form of double marginalization in which the royalty rate acts as a tax on the franchisee. The second is the possibility that a low price at one store can increase system-wide demand by building a reputation of being a low-price chain. Because the franchisor's profits are more tied to system-wide sales than a franchisee's are, the franchisor will tend to charge lower prices.

Lafontaine and Shaw (1999) use a panel data set to analyze how fixed franchise fees and royalty rates change over time for a given franchisee. They find that, in general, both types of franchise fees are persistent over time.[7] In subsequent work, Lafontaine and Oxley (2004) find that chains that sell franchises in both the United States and Mexico typically use the same fee structure in both countries.

Brickley (1999) builds and empirically tests a model that attempts to explain common features of franchise contracts. He then attempts to explain the variation across franchisors in the share of company-owned stores. Brickley first finds that many features of franchise contracts, including advertising expenditure requirements and a preference for franchisees who are actively involved in store operations, are most commonly observed when negative inter-franchisee externalities are especially important. He then finds that the variation in company ownership can be best explained by franchisee liquidity constraints and risk preferences; this supports the theory introduced by Kaufmann and Lafontaine (1994).

[7] In the case of fixed fees, because the nominal amount typically does not change over time, the inflation-adjusted amount tends to decrease.

While most literature emphasizes the franchisor's decision process, Kaufmann (1999) focuses on an entrepreneur's decision of whether to buy a franchise or open an independent store. He follows individuals who expressed an interest in entrepreneurship over a span of three years and compares the stated preferences of those who eventually bought franchises with those who did not. He first finds that individuals who go into entrepreneurship (either as a franchisee or as an independent store owner) tend to do so because they have strong preferences for independence and being personally involved in running a business. He also finds that entrepreneurs who go into franchising do so because they are attracted to the financial benefits of franchising, specifically the fact that franchising is considered to be a lower-risk option and that financing is more easily available for franchisees than for other entrepreneurs.

Chaudhuri, Ghosh, and Spell (2001) attempt to explain the fact that many franchisors choose to have both company-owned and franchisee-owned stores.[8] They build a theoretical model with two significant assumptions: store locations vary in quality and the franchisor knows more about location quality than the franchisees. Their results indicate that the franchisor will choose to own the stores in the best locations and franchise the stores at the remaining locations. They use these results to explain U.S. Chamber of Commerce survey data, which show that, for a given sector, company-owned stores tend to have higher revenues than franchised stores.

Like Kaufmann, Affuso (2002) focuses on modeling the decision process of potential franchisees.[9] Using survey data from the U.K, she finds that stores which are franchised generally have aspects which franchisees find desirable. For example, chains with lower up-front costs and those which have been in business longer represent lower-risk invest-

[8] This is different from previous research, including Brickley (1999), that investigates why the share of company-owned stores varies among chains.

[9] This is substantially different from Chaudhuri, Ghosh, and Spell (2001), who essentially assume that all bargaining power lies with the franchisors; in their model, franchisees are always willing to take whatever location is offered to them.

ments and are more likely to be franchised.

Kalnins (2004) examines the consequences of encroachment, which occurs when a franchisor allows for the opening of new franchised stores near existing stores owned by a different franchisee. Theory predicts that encroachment is a result of misaligned incentives: a new store will increase system wide sales (which benefits the franchisor) while decreasing store-level profits (which hurts the franchisee). Kalnins uses revenue data from the Texas lodging industry to empirically evaluate the effects of encroachment. He finds that, as expected, the entry of a nearby establishment affiliated with the same franchisor causes a decrease in the existing franchisee's sales. He also finds that this decrease in revenue is considerably larger than the decrease in revenue that occurs when a chain that does not use franchising opens a new motel near an existing motel. The author suggests that this could be because inter-franchisee competition will result in lower prices, while two stores that share the same owner will not be subject to such competition.

Kalnins and Lafontaine (2004) look at openings of fast food restaurants in Texas over a 15 year period in order to determine how franchisors allocate new stores among existing franchisees. They find that stores are most likely to be assigned to existing franchisees with stores which are either geographically close or demographically similar to the market of the new store. They also find that, when the franchisor chooses to own a store, it is often the case that the franchisor owns nearby stores. Thus, franchisors tend to assign new stores to the owner of nearby existing stores, a statement that holds true whether that owner is a franchisee or the franchisor. This supports the hypothesis that local expertise is an important reason for why franchising exists.

Kalnins and Mayer (2004) also investigate the importance of local expertise. They find that local experience by the owner is associated with lower failure rates of pizza restaurant franchises, while there are no benefits from non-local ownership experience. They also find that franchisees benefit from the local expertise of the franchisor if the franchisor owns nearby stores. This indicates that local expertise is important for store success, but general ownership experience is not.

Yin and Zajac (2004) incorporate theories from the strategy literature into their analysis of franchising. They suggest that, for a given chain, franchisee-owned stores will tend to pursue more complicated business strategies, because franchisees will be more "highly motivated, flexible, and autonomous" and that pursuing these strategies will lead to higher store profits. They use sales data from a pizza chain and consider restaurants that offer both dine-in and delivery to be stores using a complicated business strategy. They find evidence that supports both of their hypotheses. Interestingly, they find that, while pursuing a complicated strategy is revenue increasing for a franchisee-owned store, it is revenue decreasing for a company-owned store. One important caveat is that data limitations prevent the authors from being able to model how each store chooses its strategy (for example, why some company-owned stores offer both dine-in and delivery, even though the regression results indicate that this strategy is revenue decreasing for company-owned stores).

Lafontaine and Shaw (2005) use a panel data set of chain and store characteristics for over 1,000 franchisors to examine how franchisors choose what share of stores should be company-owned. First, they find that, for established franchisors, the share of franchised stores stays roughly constant over time, even as the chain expands. This suggests that franchisors have a preferred share of company-owned stores. They next find that this share varies widely across firms. The authors next attempt to explain the causes of this variance. They find that chains with more valuable brands have a higher share of company-owned stores, and suggest that is because those chains are more subject to franchisee free riding.

Yeap (2005) finds that company-owned restaurants sell more alcohol as a share of total revenue than do franchised restaurants. She also finds that, all else equal, serving alcohol makes a restaurant more likely to be franchised. For restaurants that serve alcohol, having bar service decreases the probability that the restaurant is franchised. She considers selling alcohol and performing bar service to be examples of complex tasks, and, therefore, finds mixed evidence on the correlation between task complexity and franchisee ownership.

Fuld (2011) empirically tests the theory that, relative to a franchisor, franchisees are local experts and therefore are better able to customize their stores to their local markets. He does this using transaction-level sales data for a pizza delivery chain that has both company-owned and franchisee-owned stores. He first builds a spatial model to estimate store-level demand for each store. He then examines store-level pricing and promotional strategies and compares price changes with demand shocks. He finds that franchised stores are more likely to respond to demand shocks by adjusting prices appropriately, which supports a theory of local expertise.

Argyres, Bercovitz, and Zanarone (2016) investigate the prevalence of multi-unit franchising, which occurs when a single franchisee owns multiple stores. They first note that this arrangement seems to negate one of the main benefits of franchising: an owner who is both highly motivated (due to the structure of franchise contracts) and intimately familiar with store operations. This happens because a franchisee who owns multiple stores will be unable to properly supervise each store and will instead hire managers to oversee store operations, which will open up the same moral hazard problems that franchising is intended to solve. Their theory predicts that multi-unit franchisees are less likely to free ride on the franchisor's brand because the negative spillovers from a diminished brand will affect all of the franchisee's stores. They suggest that this will result in greater cooperation (in the form of brand maintenance) by the franchisor. They conclude with a prediction that multi-unit franchising will be lead to a better, more stable relationship between a franchisor and a franchisee. They test this using a data set which contains information on litigation between franchisees and franchisors. They find that multi-unit franchisees are less likely to be involved in ligation against a franchisor, which supports their theory that multi-unit franchising increases cooperation between franchisees and franchisors.

1.1.3 Models of Spatial Competition

The structural model in the third section of my paper focuses on consumers choosing between differentiated retailers, in this case restaurants. Some of the differences are due to different product offerings and some are due to spatial differences. These spatial differences are especially important, as consumers' travel costs and their varying distances from different restaurants help identify the parameters of the model. Here I discuss some empirical research that incorporates spatial differences between firms.

Many early models of competition between firms selling non-identical products used spatial differences as a source of horizontal product differentiation. These models include Hotelling (1929), Lerner and Singer (1937), and Salop (1979). More recent research has focused on empirically estimating entry games where firms select product attributes including geographic location. Manuszak (2001) incorporates individuals' locations and travel costs into a model of demand which he uses to analyze the effect of oil company mergers on fuel prices in Hawaii. Davis (2006) estimates the demand for movie theaters, incorporating consumer preferences for visiting theaters near where they live. He finds that spatial differences provide many theaters with substantial market power and that many theaters are local monopolies. Seim (2006) uses data on the locations of video rental stores to empirically model the importance of geographic differences on the entry decisions of firms selling otherwise identical products. McManus (2007) models demand in a specialty coffee market and estimates consumers' travel costs. Gowrisankaran and Krainer (2011) find that spatial differences among ATMs are a source of market power for their owners.

One paper related to franchising that incorporates spatial competition is Kalnins (2003). Using data on store locations and prices, he constructs a model that uses geographic differentiation to examine the degree of substitutability between the hamburgers of various fast food restaurants. He finds that hamburgers sold by different chains are not close substitutes, but hamburgers sold by nearby stores affiliated with the same chain are substitutes. Thus, he provides evidence that inter-franchisee competition is an important consideration for franchisors and franchisees.

Holmes (2011) and Ellickson et. al. (2016) use methods that are especially relevant for my research. Holmes models individuals choosing between different Wal-Mart stores and an outside option. Each store gives each individual a utility that is a function of store characteristics and travel distances. The utility function includes a logit error term, which leads to logit choice probabilities for each individual. Aggregating consumer behavior leads to predicted revenues for each Wal-Mart store. Ellickson et. al. extend this model by allowing for competition between firms. Using grocery store revenue data, they estimate the effects of potential mergers. In both cases, the authors have store-level sales data for retailers that sell a wide range of products, but they do not have detailed information on prices and quantities; I face the same data limitations, which is why I base my model on theirs.

1.2 Institutional Details

As of 2014, there are over 750,000 franchised establishments in the U.S., earning over $800 billion in revenues and employing over 8 million people (*IHS Global Insight*, 2015). Franchising is used in a variety of industries including restaurants, fitness centers, convenience stores, and hotels. While contract forms vary across companies, the most common fee structure is one in which the franchisee pays the franchisor a fixed fee for the right to open a store and then a royalty that is a fixed percentage of sales. For a given franchisor, the fixed fee and royalty rate are usually the same for all franchisees and all stores. Furthermore, for a given franchisor, franchise fees are generally persistent over time.

In the United States, the restaurant industry accounts for 4 percent of GDP and 47 percent of total food sales, with projected 2016 sales of $783 billion (National Restaurant

Association, 2016). In a 2010 USDA survey, over 80% of individuals reported eating a meal prepared away from home in the last week, and over 20% reported eating six or more meals prepared away from home. After fast food restaurants, casual dining restaurants make up the largest segment of the restaurant industry. Casual dining restaurants are characterized by moderate prices, full table service, and the availability of a variety of alcoholic beverages. With over 1,800 restaurants and $4.7 billion in annual revenue, Applebee's is the largest casual dining chain in the United States. Because I intend to measure the effect of franchising on Applebee's, I focus on Applebee's and its closest competitors. Specifically, I look at casual dining restaurants that, like Applebee's, are affiliated with a national chain and have a wide variety of menu items. In addition to traditional American fare like hamburgers and steak, their menus include items inspired by Italian, Asian, and Mexican cuisine. I include the following stores in this grouping: Buffalo Wild Wings, Chili's, and T.G.I. Friday's. Together with Applebee's, these are four of the top seven casual dining chains in the United States. Table 1.2 shows a selection of menu items and prices for each of these four chains; the table shows that the chains have similar menu items and similar prices. As of 2015, the average check size at Applebee's was $12.42 and the average check size at Chili's was $13.99.[10] While franchising is very common among fast food chains, it is used less frequently by casual dining chains. For example, all T.G.I. Friday's, Olive Garden, Outback Steakhouse, and Red Lobster restaurants in Texas are company-owned. About half of the Buffalo Wild Wings restaurants and all of the Applebee's and Chili's restaurants in Texas are franchised. One final piece of relevant information is that the casual dining industry is known to be highly competitive and characterized by low profit margins; in 2010, full-service restaurants with average check sizes of less than $15 had a median pretax profit margin of 3% (National Restaurant Association, 2010).

[10]While average check sizes for Buffalo Wild Wings and T.G.I. Friday are unavailable, given the similarity in prices among the chains, it is likely that average check size is comparable.

For the casual dining chains that use franchising, fees follow the standard format discussed above and are identical for all stores affiliated with a given franchisor. As shown in Table 1.1, fees are similar across many large chains. Franchise contracts typically have a long term, around 20 years, so the fixed fee represents a small share of the total fees paid. Because franchisors typically aim to maintain a consistent brand identity, franchise contracts often contain specific rules about conforming to franchisor policies. As a result, restaurants affiliated with the same chain tend to have similar menu offerings and prices.[11]

1.2.1 Sale to IHOP

In 2007, there were 59 company-owned Applebee's stores and 33 franchised Applebee's stores in Texas. In February of that year, Applebee's, a publicly traded company, put itself up for sale. Five months later, IHOP Corporation agreed to purchase the chain for $1.9 billion. IHOP Corporation is the parent company of IHOP, the largest chain restaurant in the family dining category.[12] IHOP Corporation has a strong preference toward franchising its stores; at the time of the sale, nearly 100% of IHOP restaurants were owned by franchisees. Shortly after the sale, IHOP Corporation began selling its company-owned Applebee's stores to franchises. By the end of 2008, all Applebee's stores in Texas were franchised.[13] Annual store counts by ownership type are presented in Figure 1.1.

One relevant question is why IHOP chose a different ownership strategy than Applebee's had chosen. A possible indication of IHOP's reasoning is found in a presentation

[11] An example of Applebee's attempt to balance this preference for uniformity with a desire to cater to local markets can be found in its 2013 franchise disclosure document. Applebee's creates a uniform menu for all of its stores and requires all franchisees to use it. However, the chain also allows for franchisees to "propose additional items that appeal to local trends and traditions."

[12] The main difference between the family dining category and the casual dining category is that family dining restaurants typically do not sell alcohol. Following the sale, IHOP Corporation changed its name to DineEquity. Throughout the paper, I use "IHOP" to refer to the parent company that owns Applebee's.

[13] This is not a single-state phenomenon; Applebee's 2014 10-K states that 99 percent of IHOP and Applebee's stores are franchised.

to investors given by IHOP in 2012 regarding the decision to sell company-owned Applebee's stores to franchisees. In the presentation, IHOP states "[t]he Company believes a more heavily franchised business model requires less capital investment and reduces the volatility of its cash flow performance." Thus, IHOP may have given greater weight to those concerns than it did to a simple comparison of whether, for a given store, its profits would be greater as a store owner or as a franchisor. Also in the presentation, IHOP predicted that each restaurant sale would result in an annual cost savings of $90,000 due to reduced administrative costs and reduced capital expenditures.

1.3 Motivational Model of Ownership Selection

In this section I construct an model of a profit-maximizing franchisor who decides whether a given store should be company-owned or franchised. While I do not attempt to estimate this model, it provides intuition that is used in my empirical models. The model gives two significant results. First, it predicts that the franchisor will choose to own stores at the best locations and franchise stores at the other locations. Second, it highlights the sort of exogenous variation needed to give an unbiased estimate of the franchise effect.

A franchisor plans to open a store at location j and must decide whether the store should be company-owned or franchised. If store j is company-owned, the present value of all future revenues for store j at the time of store j's opening is

$$r_j^C = \sigma a_j + \xi_j, \tag{1.1}$$

where a_j contains location-level attributes that are observed by the econometrician and ξ_j represents location-level determinants of revenue that are not observed by the econometrician. Components of a_j may include demographics such as the population and average income of the local market; σ is a vector of parameters. The ξ_j term is included because it is likely that store revenues are determined by factors that are known to the franchisor but unobserved by the econometrician (e.g. the quality of food at competing restaurants).

As discussed earlier, there are reasons to believe that a franchised store will outperform a company-owned store. I define β as the present discounted value of all additional revenues earned by a store if it is franchised. So, revenue for a franchised store is

$$r_j^F = r_j^C + \beta.$$

Costs are normalized to zero, so maximizing revenue is equivalent to maximizing profit. For a company-owned store, the franchisor keeps all revenue as profit:

$$\Pi_j^C = r_j^C. \tag{1.2}$$

For a franchised store, the franchisor earns a share, v, of all revenue collected as well as a fixed fee, K. Franchisor profit from a franchisee-owned store is

$$\Pi_j^F = v\left(r_j^C + \beta\right) + K.$$

The franchisor will choose to franchise store j if $\Pi_j^F > \Pi_j^C$. This occurs when

$$r_j^C < \frac{K + \beta v}{1 - v}. \tag{1.3}$$

Thus, stores with low values of r_j^C will be franchised. The intuition for this prediction is that the franchisor receives all of the profits of a company-owned store and only a fraction of the revenue of a franchised store. For the best locations (those with the highest values of r_j^C), the franchisor is willing to give up the fixed fee and a share of the revenue in order to keep all of the location's profits.[14]

To illustrate the impact that this selection has on attempts to measure β, consider two stores, k and l, that have identical observables, $a_k = a_l$. Store k is company-owned and store l is franchised. I define r_j as the revenue of store j and f_j as a dummy variable equal to 1 if store j is franchised:

$$r_j = f_j r_j^F + (1 - f_j) r_j^C.$$

The difference in store revenues is

$$r_l - r_k = \xi_l - \xi_k + \beta.$$

If the two stores have identical unobservables, or if ownership is randomly determined such that

$$E[f_j | \xi_j] = E[f_j], \tag{1.4}$$

then $r_l - r_k$ is an unbiased estimate of β. However, it is likely that ξ_j will be correlated with the ownership decision. There is a direct relationship between ξ_j and r_j^C shown in (1.1). As shown in (1.3), stores with high values of r_j^C will be company-owned, so it is likely that $\xi_k > \xi_l$. This means that an estimation of $\hat{\beta} = r_l - r_k$ is likely to be biased downward. Observing both r_j^C and r_j^F for some store j would overcome this obstacle. Because this will involve observing the same store at different times, I define f_{jt} as a dummy variable equal to 1 if store j is franchised at time t. The condition for a valid instrument can now be shown as

[14]The model makes two significant assumptions. The first is that there are no costs. The second is that β is an additive increase to profits instead a multiplicative increase. (A multiplicative increase would be shown as $r_j^F = \beta r_j^C$.) However, either of these two assumptions can be loosened. While the condition for franchising shown in (1.3) will change, the conclusion that stores lower values of r_j^C are more likely to be franchised will remain true. See Chaudhuri, Ghosh, and Spell (2001) for a different model which generates similar predictions.

$$E[f_{jt}|\xi_j] = E[f_{jt}] \tag{1.5}$$

for some store j that changes ownership. The best way to achieve this would be for an exogenous event uncorrelated with store-level unobservables to cause the ownership of a store to change. The sale of Applebee's to IHOP satisfies these requirements; after 2008, $E[f_{jt}|\xi_j] = E[f_{jt}]$ for all stores because $f_{jt} = 1$ for all stores.

The sale of Applebee's to IHOP and the subsequent franchising of all company-owned stores allows me to identify the effect of franchising. This event has two qualities that make it a valid instrument. First, it results in some stores being observed both as company-owned and franchised. Second, all stores are franchised by the end of 2008, so the post-2008 ownership of a store is uncorrelated with its unobservables.

1.4 Data

I next describe the three data sets used in my analysis. The first is store-level alcohol revenues for all bars and restaurants in the state of Texas. The second is zip code level population and income data available from government sources. The third consists of disclosure documents required by law to be published by franchisors and furnished to potential franchisees. Summary statistics for store revenues and zip code level populations during the first quarter of 2013 are shown in Table 1.3. More detailed information regarding sample selection and geocoding of locations can be found in Appendix B.

Texas mixed beverage sales tax

My research covers restaurant franchising in the state of Texas, specifically those stores that sell liquor. As of 2015, there are over 43,000 restaurants in Texas with 2016 projected sales of $52.4 billion.[15] In 2013, there were over 15,000 restaurants in Texas that sold liquor, generating more than $5.5 billion in alcohol sales.

Texas imposes a mixed beverage sales tax on all establishments selling liquor to be

[15] National Restaurant Association, 2016.

consumed on premises, primarily bars and restaurants. While the tax is only imposed on establishments that sell liquor, those establishments must pay the tax on all alcoholic beverages sold, including beer and wine. This tax is equal to a fixed share of revenue (14 percent during my sample period) from the sales of alcoholic beverages. The amount collected is publicly available on a per-store, per-month basis. I use data covering 2004 through the third quarter of 2013.

The data have several features. They cover all restaurants with a liquor license, rather than only a single firm. By dividing the tax revenue by the appropriate tax rate, I obtain store-level alcohol revenues. By observing when firms appear and disappear in the data, I can infer when firms enter and exit. Finally, the data include locations for all firms in the form of street addresses; I use ArcGIS software to identify latitude and longitude coordinates for each store. The data set also has some limitations. The most significant is that it only includes alcohol sales, rather than all revenues received by the restaurant. Thus, I assume that alcohol sales are a proxy for total sales. It is worth noting that alcohol sales typically have a large impact on store success, because alcohol sales generate substantially higher profit margins than food sales.[16] A second limitation is that the data include only revenues, rather than prices and quantities. This means that I cannot differentiate between a store that sells a small quantity of high-priced drinks and a store that sells a large quantity of low-priced drinks.

For Applebee's, Buffalo Wild Wings, Chili's, and T.G.I. Friday's, I used franchise disclosure documents, company websites, and online mapping tools to ensure that all restaurants were properly identified and geocoded. I confirmed that these chains sell liquor and therefore are included in the tax data. (Furthermore, franchise disclosure documents indicate that these chains will not allow a store to open without a liquor license.) The number of stores affiliated with each chain at the beginning of each year

[16] In 2010, a Nation's Restaurant News study calculated that median alcohol sales were 350% of costs, while median food sales were 144% of costs.

is shown in Figure 1.2. The chains each have similar average per-store revenues, with Buffalo Wild Wings having the highest per-store revenues and Chili's the lowest. Chili's, which originated in Texas, has more outlets in Texas than the other chains. Yearly average first quarter per-store alcohol revenues for each chain over time are shown in Figure 1.3.

Stores other than the four chains mentioned above are grouped together at the zip code level, with each group representing an outside option. The average outside option contains 14 stores, with the largest outside option containing 236 stores.

Population data

I use federal income tax return data to estimate annual zip code level populations from 2003 to 2013. The Internal Revenue Service (IRS) releases information on the number of tax returns filed in each zip code. Also included in this data is the number of claimed exemptions filed in each zip code, which the IRS states serves an estimate for population.[17] Because this estimate is not exact, I multiply each zip code's estimated population by a constant to ensure that total estimated state population matches the actual population each year. During my sample period, this constant ranged from 1.04 to 1.09. Thus, the allocation of population among zip codes may be incorrect, but total statewide population will be correct.[18] I next find the latitude and longitude of the centroid of each zip code using MABLE, an online database maintained by the Missouri State Library. In 2013, there were 1,623 zip codes in Texas with an average population of 16,176 and a median population of 8,672. More densely populated areas contain zip

[17]The number of claimed exemptions in a region has frequently been used in population estimates. The U.S. Census Bureau uses this information when calculating annual county-level population estimates and when estimating various statistics, such as poverty rates and health insurance coverage as part of SAIPE (Small Area Income and Poverty Estimates). See Sailer and Weber (1998) for additional discussion.

[18]While a more accurate population count would be preferred, the finest level where population is annually tallied by the U.S. Census Bureau or the state of Texas is by county. Because travel cost is a key component of my analysis, it is important to be as precise as possible when modeling where consumers live. There are many more zip codes than counties, so using zip code level populations gives a better approximation of where people live.

codes that are geographically smaller, while in less populated regions, a single zip code can span a very large area.

Texas experienced significant population growth during my sample period, with statewide population increasing from approximately 22,300,000 to approximately 26,450,000. This growth varied significantly among zip codes, with a quarter of zip codes experiencing no population growth and a quarter of zip codes experiencing a population increase of 20 percent or more. This illustrates the importance of using a model that separates revenue changes due to franchising from revenue changes due to population growth.

I use annual per-capita income data from the U.S. Census Bureau. These data are not available at the zip code level. So, when zip code level per-capita income data is required by the model, I assume each zip code has a per-capita income equal to the per-capita income of the county where the zip code is located. Income quartiles are determined by assuming that each individual has an income equal to the per-capita income of their county and then finding cutoff values such that 25%, 50%, or 75% of individuals have incomes below that value. Income quartiles over time are graphed in Figure 1.4; numbers indicate the lowest income for an individual in each income quartile.

Franchise disclosure documents

Federal law requires franchisors to create a franchise disclosure document (FDD) and distribute the FDD to all potential franchisees. FDDs contain information about the franchisor and the business relationship between the franchisor and its franchisees. Several states require all franchisors operating in that state to submit an FDD to the state, in which case the FDD often becomes a public record. Each FDD includes a list of all franchisee-owned stores.[19] I use Applebee's FDDs from 2006 and 2010-2011 to determine which stores were company-owned and which were franchised prior to 2008.

[19]Most FDDs, including those for Applebee's, also list all company-owned stores.

1.5 Additional Data Discussion

Table 1.4 gives statistics on populations and alcohol sales for 2013. The ten largest counties are described individually; all other counties are aggregated together. Overall, in 2013 there were 14,816 establishments in the state that sold liquor for on-premises consumption, with total alcohol sales of $5.57 billion, which is an average of $306 per adult of legal drinking age.[20] The sale of Applebee's to IHOP occurred in 2007, which was shortly before the financial crisis of 2008 and subsequent recession. Thus, it is important to understand how the recession affected alcohol consumption and, more generally, how individuals' incomes and alcohol choices changed over time. Figure 1.5 shows statewide total sales and per capita sales from 2004 to 2013. Both figures tend to increase throughout my sample period, but these increases stall in 2008 and 2009. Figure 1.6 shows how incomes and total sales as a share of income change over time.[21] The share of income spent on alcohol stays roughly constant throughout most of my sample period; the one notable aberration is a sharp decrease in 2009.

There is substantial variance in alcohol sales among establishments. In the first quarter of 2013, the five largest sellers had average revenues of $3.57 million, while there were 197 establishments with sales of less than $1,000. It is also worth noting that none of the top ten sellers of alcohol are traditional bars or restaurants; all of them are hotels, convention centers, airports, or sports arenas. I choose not to remove any of these large sellers from my analysis for two reasons. First, it is not clear what a reasonable removal strategy would be, and second, these large sellers are not actually outliers in my estimation. This is because I estimate both the linear model and the structural model using logged sales, rather than actual sales. As shown in Figure 1.7 and Figure 1.8, while

[20] Establishment counts are taken in the first quarter of the year; because firms enter and exit throughout the year, the total number of establishments will change during each year. Similarly, whenever yearly population is used in graphs or tables, population as of the first quarter of the year is used.

[21] Because in my structural model individuals set their alcohol budget as a share of their incomes, per capita alcohol expenditures as a share of per capita income is an important metric.

a histogram of sales shows significant outliers on the right side of the distribution, no such outliers exist on a histogram of logged sales.

Finally, Figure 1.9 is a map of all chain stores in Texas in 2006. Additionally, counties in the map are shaded based on their per-capita alcohol sales. Three patterns are noticeable. First, chain stores tend to be located in areas that have high per-capita alcohol sales. The cause of this relationship is not clear; it could be that individuals who live in counties with high per-capita sales have strong tastes for alcohol, and the chain restaurants respond to those tastes by opening restaurants there. Alternatively, it could be that the existence of so many chain restaurants encourages individuals to consume more alcohol at restaurants than they otherwise would have. Second, while most stores are located in populous areas such as Dallas and Houston, there are also several stores (mostly Chili's and Applebee's) in less populous areas. These areas tend to have only one store. This may be evidence that these smaller markets can only support one chain restaurant. Third, company-owned Applebee's tend to be near other company-owned Applebee's, and franchised Applebee's tend to be near other franchised Applebee's.

1.6 Franchisor's Ownership Selection Process

As discussed earlier, past research has found evidence that, when franchisors open new stores, the franchise status of the new store tends to be identical to that of nearby stores.[22] Figures 1.10 and 1.11 show the locations of company-owned and franchised stores in Texas. The company-owned stores are mostly clustered in the Dallas and Houston areas, while franchisees own stores in large cities such as El Paso and Austin as well as in more isolated markets throughout the state.

Using Texas mixed beverage alcohol sales data from 2000 to 2014, I identify 65 new

[22] See Kalnins and Lafontaine (2004), Brickley and Dark (1987), and Minkler (1990).

Applebee's being opened.[23] For each store, I identify, at the time of opening, the existing store that is closest to the opening store. I then compare the ownership of the two stores. I exclude from my analysis any opening store that is not within 50 miles of an existing store and any opening store in which the ownership of either the opening store or the nearest existing store is unknown. This leaves 55 opening stores. Of those 55 stores, 50 have the same owner as the nearest existing store. Thus, there is significant evidence supporting the hypothesis that the franchisor prefers nearby stores to share the same owner. Full results are shown in Table 1.5. There are two possible reasons for this. First, the franchisor may wish to capitalize on the local experience of a franchisee, and second, nearby stores will be easier for an existing franchisee to monitor.

It is useful to compare these results to the results of the theoretical model presented in Section 1.3. In that section, the ownership of each store was determined solely by the quality of each location, with quality being independent of the ownership of the store. In order for this theory to be consistent with the observed ownership patterns, it would need to be the case that location quality tends to be very similar at proximate locations. For example, all Applebee's stores in El Paso County were franchisee-owned prior to 2008. According to the model, this means that all El Paso locations are low-quality. Similarly, all Applebee's stores in Dallas County were company-owned prior to 2008 and, therefore, are predicted by the model to be high-quality. Given the array of location types within a county,[24] it seems unlikely that the worst location in Dallas County is better than the best location in El Paso County. Instead, it seems probable that the franchisor's ownership decision depends not just on the quality of the location but on the owner of nearby stores as well. This does not necessarily mean that the franchisor is

[23] Note that this is a longer period of time than the data I use throughout my other analyses. This is because some of the demographic data used in those models was only available for a subset of those years. I consider a store's opening date to be the first quarter that it has alcohol sales recorded in the data set.

[24] For example, El Paso County contains Applebee's stores in strip malls, outside of shopping malls, in residential areas, and next door to airport hotels.

not pursuing a profit-maximizing ownership strategy. Instead, it may indicate that each store's potential revenue is highly dependent on the local expertise or monitoring ability of its owner.

Most importantly, these results do not affect the most important prediction of Section 1.3: store ownership is likely correlated with unobservables. The reason that this is likely still true is because, even if unobservables do not directly influence the ownership decision because the impact of unobservables on profit is small relative to the impact of a local owner (which, given that the ownership of a new store is so highly correlated with the ownership of the nearest existing store, appears to be the case), it is likely that nearby stores have similar observables. Continuing the earlier example, it is likely that the unobservable determinant of revenue at a given El Paso Applebee's is closer to the unobservable component at another El Paso Applebee's than it is to the unobservable component at a Dallas Applebee's, because the factors that determine this unobservable (such as, for example, quality of competing restaurants or grocery stores, religious beliefs about alcohol, and socioeconomic factors not included in my population demographics) will be similar for nearby stores.

While the ownership decision for new stores added during my sample period appears to be driven by the ownership of nearby stores, it remains to be seen why, for example, Applebee's chose to use franchisee ownership for stores in El Paso County but not stores in Dallas County. I next investigate differences between "company ownership" counties and "franchisee ownership" counties. In the fourth quarter of 2006 (the last quarter before Applebee's put itself up for sale), there were 28 counties that contained company-owned stores and 19 counties that contained franchised stores. There were a total of 59 company-owned stores and 33 franchised stores. No county contained both company-owned and franchised stores. Table 1.6 shows county-level averages for the two county types. Counties with company-owned stores tended to be larger and have higher per-capita alcohol sales. These counties also had more non-Applebee's chain stores, both in absolute terms and on a per-person basis. Because these stores are competitors, it may appear surprising that the franchisor chose to own stores in counties with more competition. However, it is possible that there are counties which have a strong taste for chain restaurant fare; this feature could have both benefited Applebee's and led to more competitors entering the market. I next compare the 2006 fourth quarter revenues of company-owned and franchised Applebee's. A histogram of revenues for both ownership types is shown in Figure 1.12. Summary statistics for the two ownership types are shown in Table 1.7. Company-owned stores have an average revenue of $80,987, while franchised stores have a slightly lower average revenue of $78,816. The median revenue of company-owned stores (79,561) is considerably larger than the median revenue of franchised stores (66,847) because the average revenue for franchised stores is skewed by some high-revenue outliers. There is substantial variance in revenues within each ownership type.

I now look for initial evidence of a benefit from franchising. I do this by comparing the 2006 fourth quarter revenues with the 2013 fourth quarter revenues for the two ownership types.[25] In my comparison, I only include stores that were open during that entire time period. This results in a sample size of 55 company-owned stores and 29 franchised stores. During these seven years, all company-owned Applebee's were sold to franchisees; thus, all else equal, if there is a positive franchise effect, I would expect the stores that were initially company-owned to have a greater revenue increase than the stores that are franchisee-owned (or, if there is a downward trend in store revenues, a smaller revenue decrease).

Summary statistics for the two time periods are shown in Table 1.8. Stores that were initially company-owned (and, therefore, experienced a change in franchise status) actually had a slightly smaller average revenue increase on a percentage basis (46% for franchised stores and 45% for company-owned stores), and stores that were franchised

[25]I use these end points because the fourth quarter of 2006 is the last quarter before the year that the IHOP sale occurred while the fourth quarter of 2013 is the last quarter for which I have revenue data.

actually had a much bigger increase in median sales (76% for franchised stores and 45% for company-owned stores). Histograms of store revenue for both ownership types and both time periods are shown in Figure 1.13.

The above statistics only consider two quarters out of a span of seven years. Next, I incorporate more time periods and look more closely at revenue trends. I first consider all stores which were open throughout the entire time period of 2004 to 2011. This includes 39 company-owned stores and 25 franchised stores. Quarterly revenues for each ownership type are shown in Figure 1.14. This graph provides some initial evidence of a franchise effect, with the stores that were initially company-owned seeing a substantial increase in revenue, both in absolute terms and relative to the always-franchised stores, following the 2007 corporate sale. However, these appears to be a slight upward trend in revenue for company-owned stores; in my analyses, it will be important to distinguish this trend from an effect of franchising. The graph also shows that the data exhibit significant seasonality. Table 1.9 provides evidence of this seasonality. It contains average annual sales for each quarter of the year. The first quarter had the highest average revenue (\$101,247), while the third quarter had the lowest average revenue (\$95,278). These averages include all quarters from 2004 through 2011 for stores which were open in all of those years.

Table 1.1: Franchise Fees for Various Casual Dining Chains

Chain	Fixed Fee	Royalty (percent)
Applebee's	$35,000	4
Buffalo Wild Wings	$40,000	5
Chili's	$40,000	4
T.G.I. Friday's	$50,000	4

Notes: These numbers come from franchise disclosure documents and do not include any additional fees paid to the franchisor, including advertising fees.

Table 1.2: Sample of Menu Items and Prices

Chain	Item	Price (in dollars)
Applebee's	Chicken Quesadilla	7.49
	Chicken Wonton Tacos	7.99
	Classic Burger	8.99
	Chicken Tenders Platter	10.49
Buffalo Wild Wings	Chicken Quesadilla	7.99
	Mini Corn Dogs	6.29
	Cheeseburger	8.99
	Crispy Chicken Tenders	10.29
Chili's	Smoked Chicken Quesadillas	10.29
	Southwestern Egg Rolls	8.59
	Oldtimer Cheeseburger	8.89
	Chicken Crispers	10.49
T.G.I. Friday's	Chicken Quesadilla	8.99
	Spinach Florentine Flatbread	9.49
	Really Good Cheeseburger	8.80
	Crispy Chicken Fingers	10.49

Notes: Prices are taken from the following Dallas outlets: Applebee's on 3565 Frankford Rd; Buffalo Wild Wings on 5000 Belt Line Rd.; Chili's on 4500 Belt Line Rd.; T.G.I. Friday's on 4951 Belt Line Rd.

Table 1.3: Summary Statistics for the First Quarter of 2013

	N	Mean	Std. Dev.	Min	Max	p25	p75
Store Revenues							
Applebee's	100	127,908	52,606	33,876	301,348	86,007	164,084
Buffalo Wild Wings	83	192,246	77,876	43,304	631,270	151,312	208,414
Chili's	208	107,038	31,658	20,791	215,367	86,430	123,094
T.G.I. Friday's	31	132,098	56,288	56,004	318,888	102,871	143,570
Outside option	973	1,343,398	3,223,087	491	58,994,137	85,178	1,347,029
Stores per outside option	973	14	19	1	236	3	19
Zip code level populations	1,623	16,176	18,320	110	115,975	2,240	25,370

Notes: Each outside option includes all non-chain stores in a zip code.

Table 1.4: County Level Statistics for 2013

County	Population	Number of Stores	Alcohol Sales (in thousands of dollars)	People per Store	Sales per Person
Harris	4,325,413	2,552	1,198,724	1,695	277
Dallas	2,459,095	1,882	837,970	1,307	341
Tarrant	1,910,975	1,441	536,603	1,326	281
Bexar	1,813,421	1,032	511,175	1,757	282
Travis	1,108,503	962	591,169	1,152	533
Collin	854,036	609	209,761	1,402	246
El Paso	829,726	400	131,629	2,074	159
Hidalgo	818,553	282	74,362	2,903	91
Denton	721,022	356	107,133	2,025	149
Fort Bend	650,693	222	76,489	2,931	118
All other counties	10,958,769	5,078	1,295,455	2,158	118
Statewide	26,450,206	14,816	5,570,470	1,785	211

Notes: All establishments found in the Texas mixed beverage sales tax data are included in the count of stores. Store counts and populations reflect data for the first quarter of 2013.

Table 1.5: Ownership of New Stores and Nearest Existing Stores

		Nearest Existing Store		
		Company-Owned	Same Franchisee	Different Franchisee
New Store:	Company-Owned	31	0	0
	Franchisee	5	19	0

Notes: Opening stores that are not within 50 miles of an existing store and opening stores in which the ownership of either the opening store or the nearest existing store is unknown are excluded from this analysis.

Table 1.6: County-Level Averages by Applebee's Ownership Type, Q4 2006

	Counties with Company-Owned Stores	Counties with Franchised Stores
Number of Applebee's	2.18	1.74
Number of Other Chain Stores	7.36	3.26
Number of Non-Chain Stores	284.50	136.53
Total Alcohol Sales	$24,800,642	$10,767,421
Population	475,502	286,301
Per Capita Alcohol Sales	$52.16	$37.61
People per Non-Applebee's Chain Store	64,631	87,737
People per Non-Chain Store	1,671	2,097
Number of Counties:	28	19

Notes: In the fourth quarter of 2006, no county included both company-owned and franchised stores

Table 1.7: Summary Statistics for Applebee's Alcohol Revenues by Ownership Type, Q4 2006

	N	Mean	Median	Std. Dev.	p25	p75
Company-Owned	59	53,591	79,561	104,858	80,987	37,392
Franchised	33	54,473	66,847	88,166	78,816	43,973

Table 1.8: Summary Statistics for Applebee's Alcohol Revenue by Ownership Type, Q4 2006 and Q4 2013

	N	Mean	Median	Std. Dev.	p25	p75
2006 - Initially Company Owned	55	83,910	80,999	36,747	58,680	108,572
2006 - Initially Franchised	29	79,157	66,847	44,757	56,584	87,675
2013 - Initially Company Owned	55	121,702	118,308	49,314	91,602	152,368
2013 - Initially Franchised	29	115,346	117,393	45,547	82,500	153,404
Initially Company Owned - Growth	55	45%	46%		56%	40%
Initially Franchised - Growth	29	46%	76%		46%	75%

Notes: Only stores which exist in both Q4 2006 and Q4 2013 are included.

Table 1.9: Average Revenue by Quarter

Quarter	Revenue
Q1: January - March	$101,247
Q2: April - June	$97,709
Q3: July - September	$95,278
Q4: October - December	$99,894

Notes: Only stores which were open in all years from 2004 through 2011 are included. Only sales figures from 2004 through 2011 are included.

FIGURE 1.1: Number of Applebee's Stores by Year

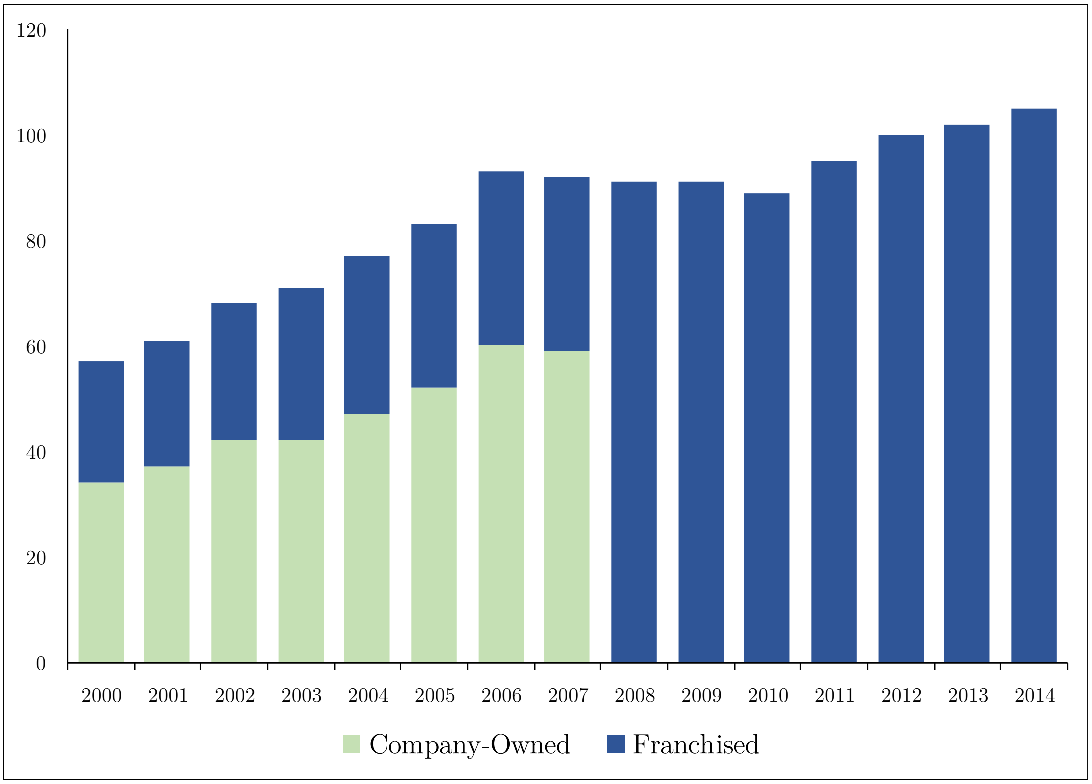
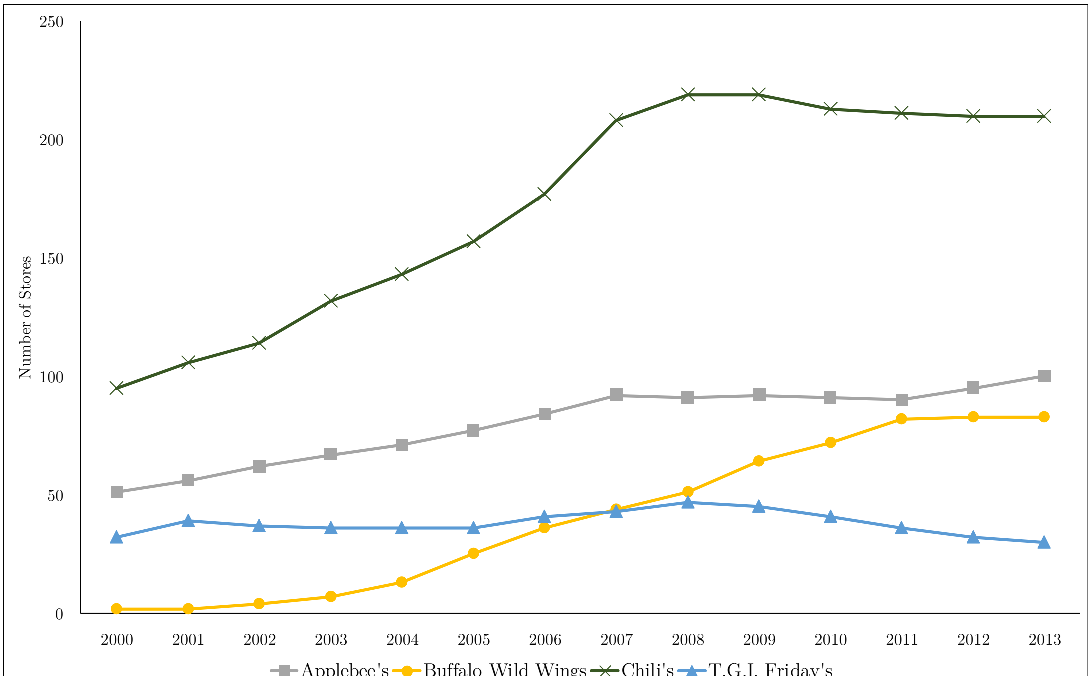


FIGURE 1.2: Number of Stores for Each Chain



Note: Graph includes all stores open in the first quarter of each year.

Figure 1.3: Average Q1 Alcohol Revenue per Store

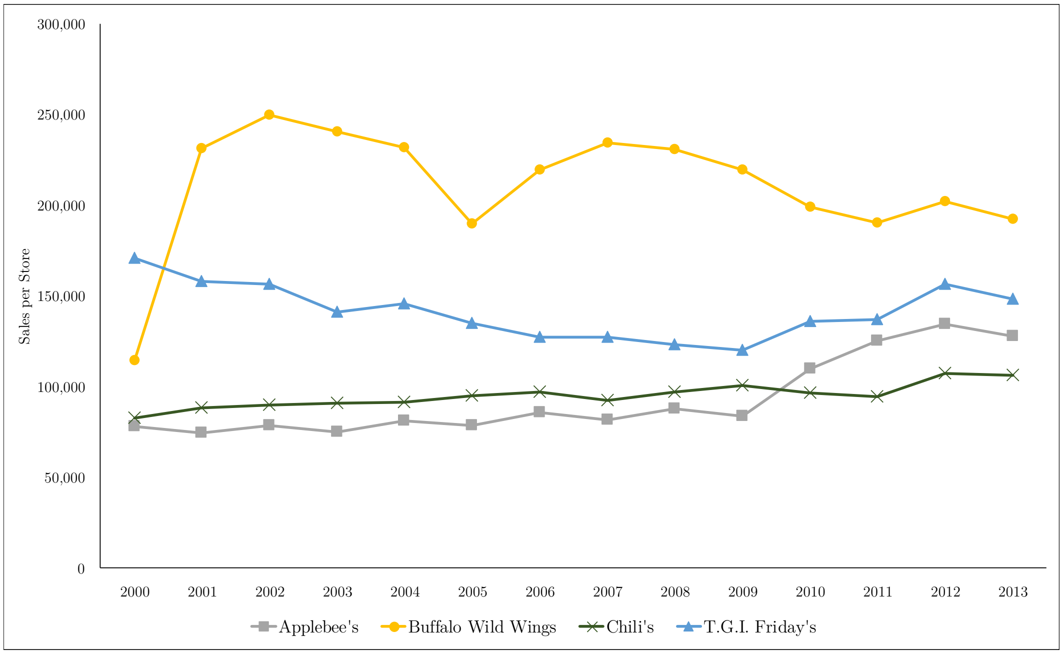


Figure 1.4: Income Quartile Cutoffs for Q1 of Each Year

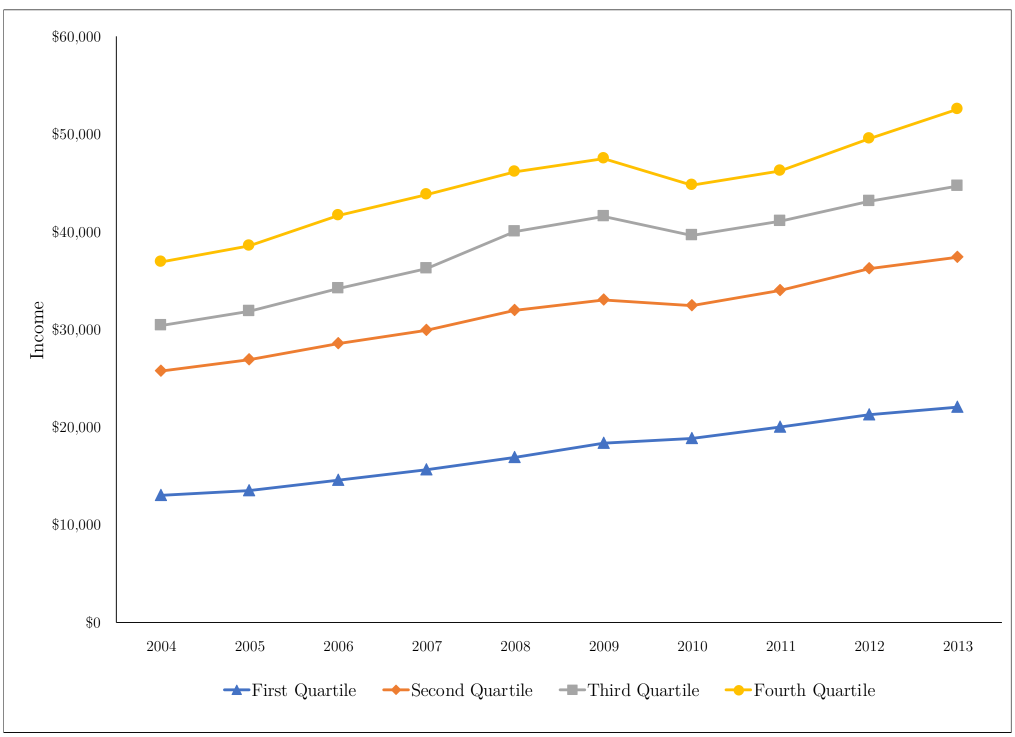
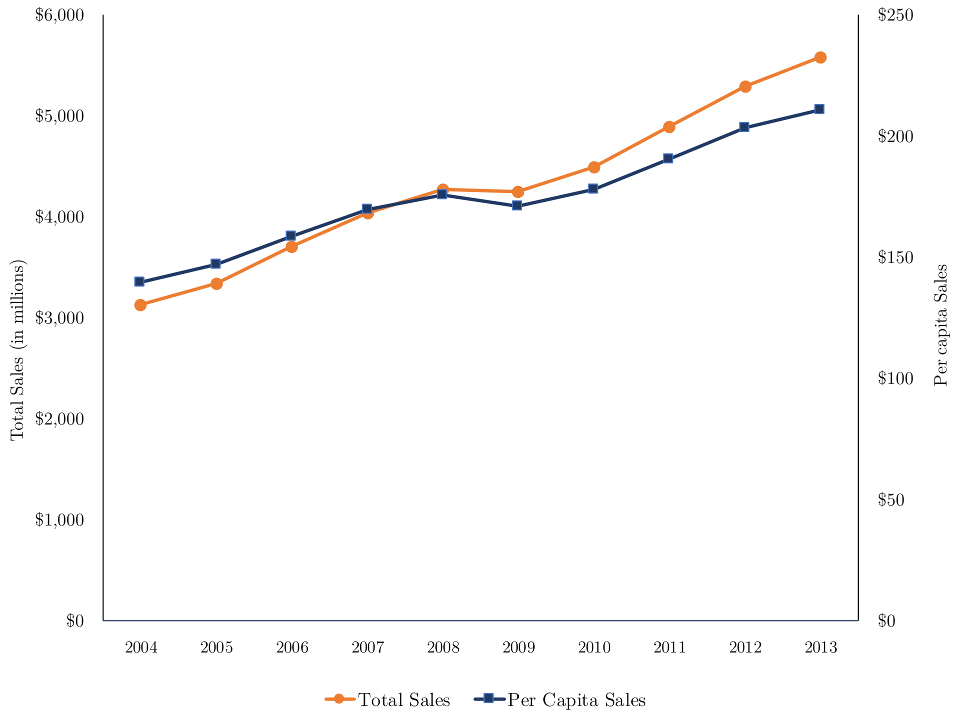
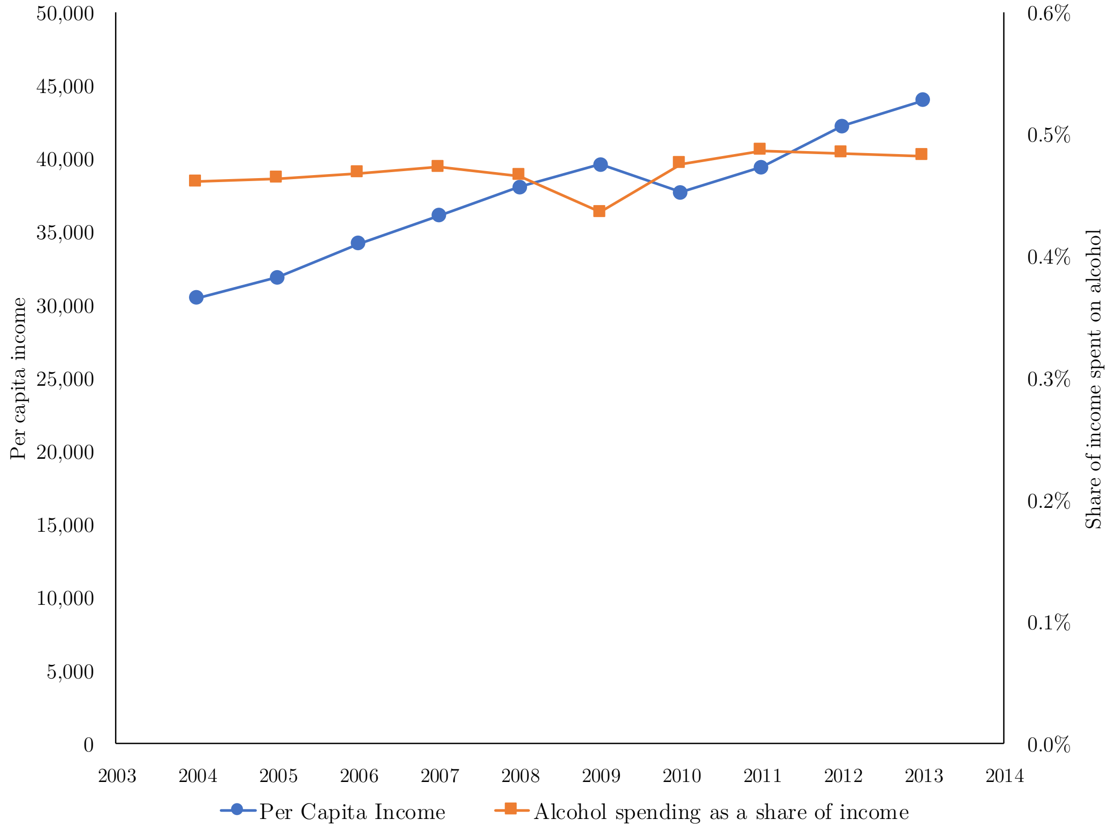


Figure 1.5: Statewide Alcohol Revenues



Notes: This includes sales at all establishments in the Texas mixed beverage sales tax data. Sales at establishments that do not allow on-premises consumption (e.g. grocery stores) and sales at establishments which sell beer or wine but not liquor are not included in the data.

Figure 1.6: Statewide Income and Alcohol Spending



Notes: This includes sales at all establishments in the Texas mixed beverage sales tax data. Sales at establishments that do not allow on-premises consumption (e.g. grocery stores) and sales at establishments which sell beer or wine but not liquor are not included in the data.

FIGURE 1.7: Histogram of Alcohol Sales for Q1 2013

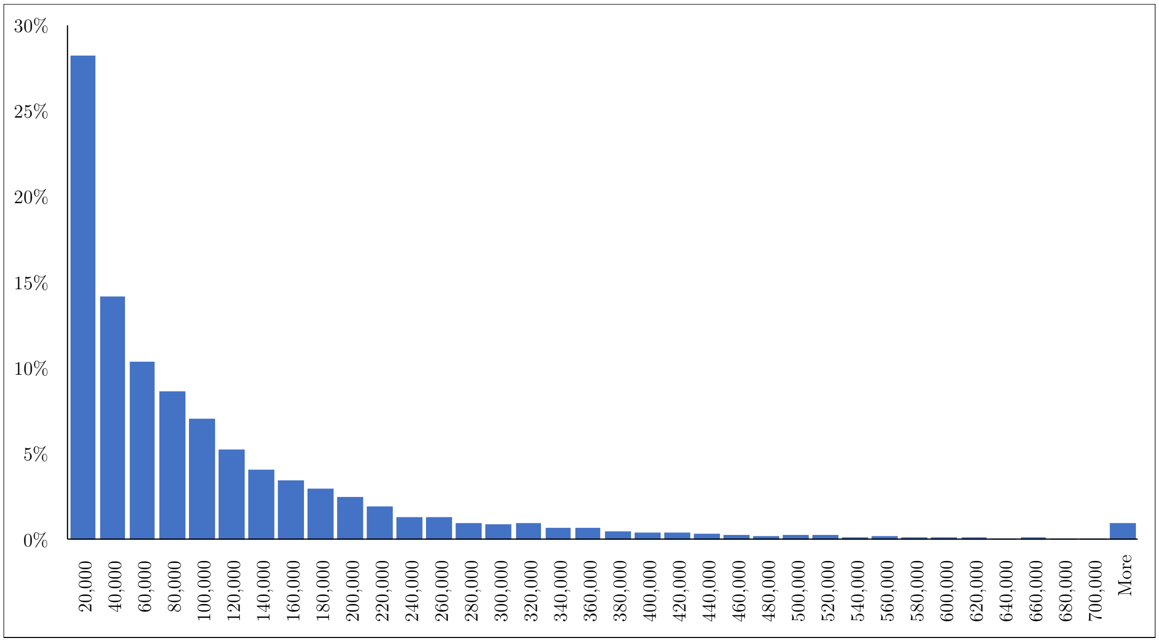


FIGURE 1.8: Histogram of Logged Alcohol Sales for Q1 2013

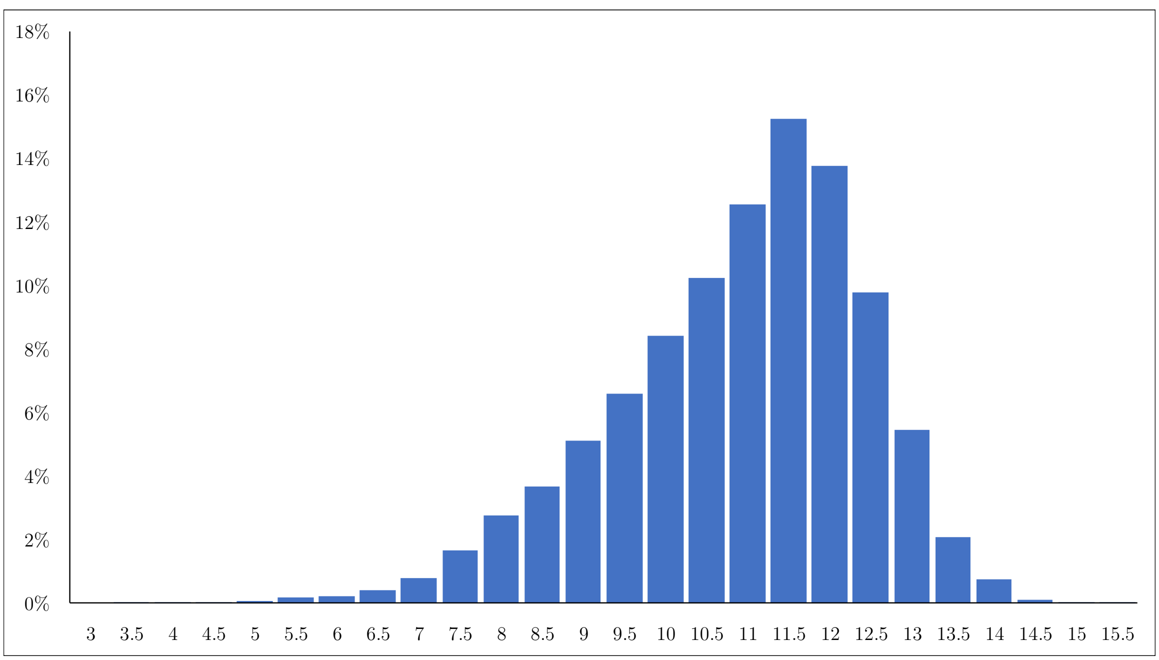


Figure 1.9: 2006 Map of Chain Stores

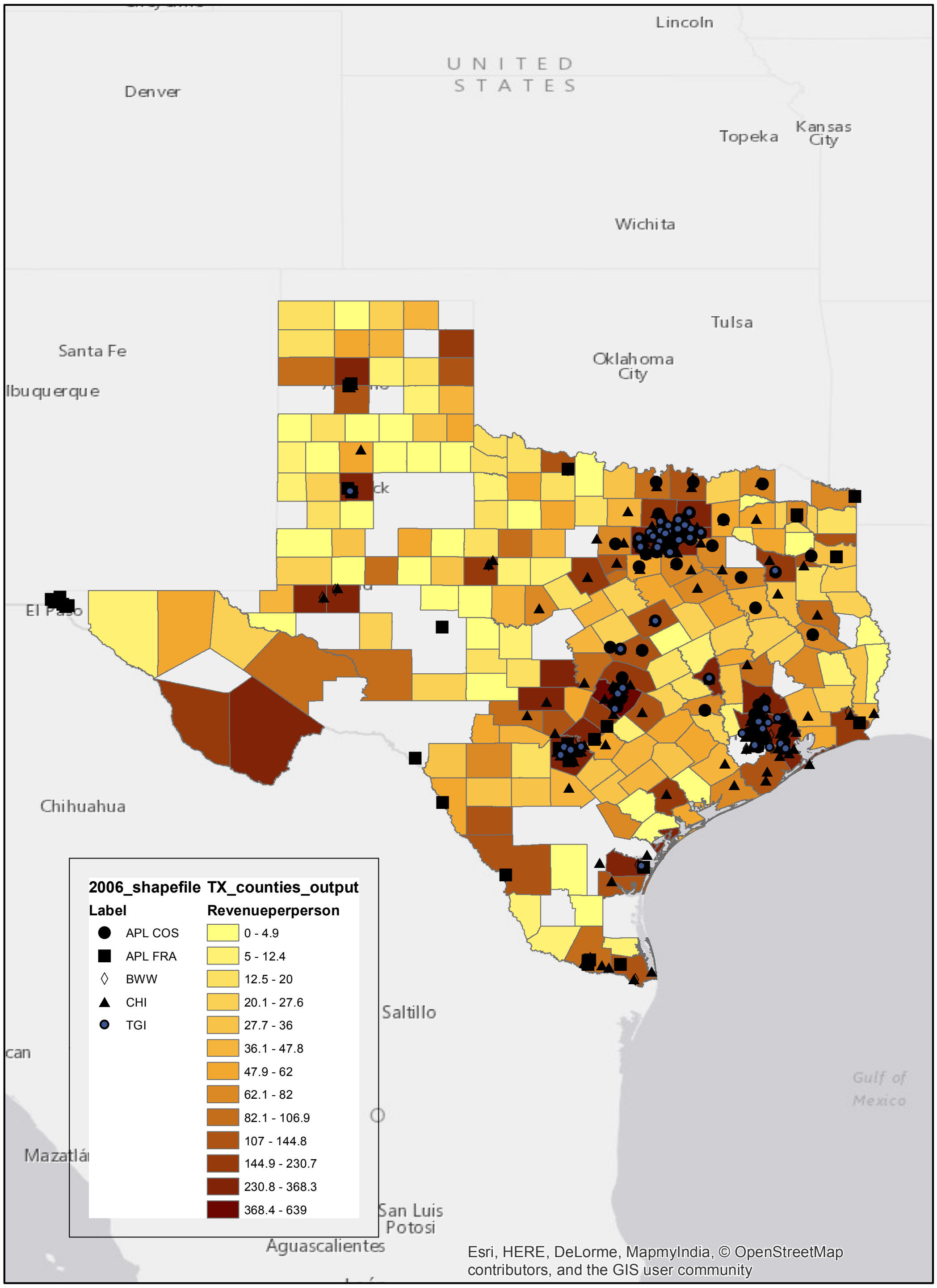
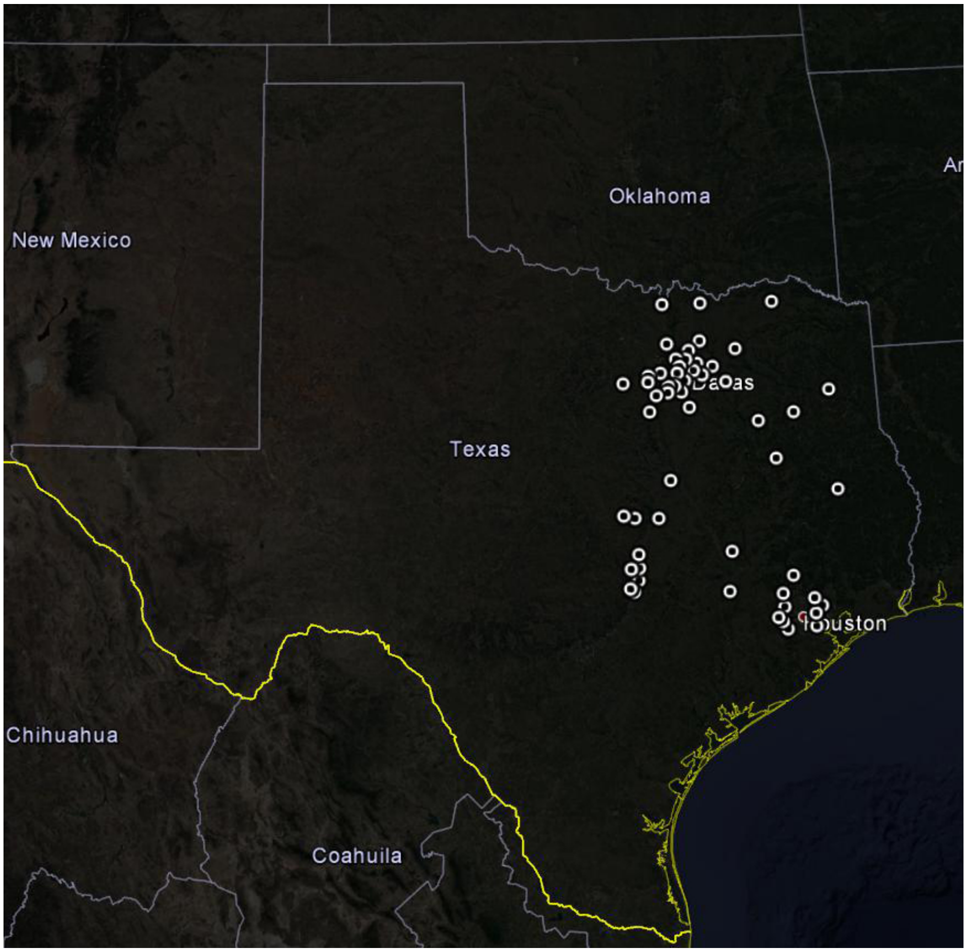
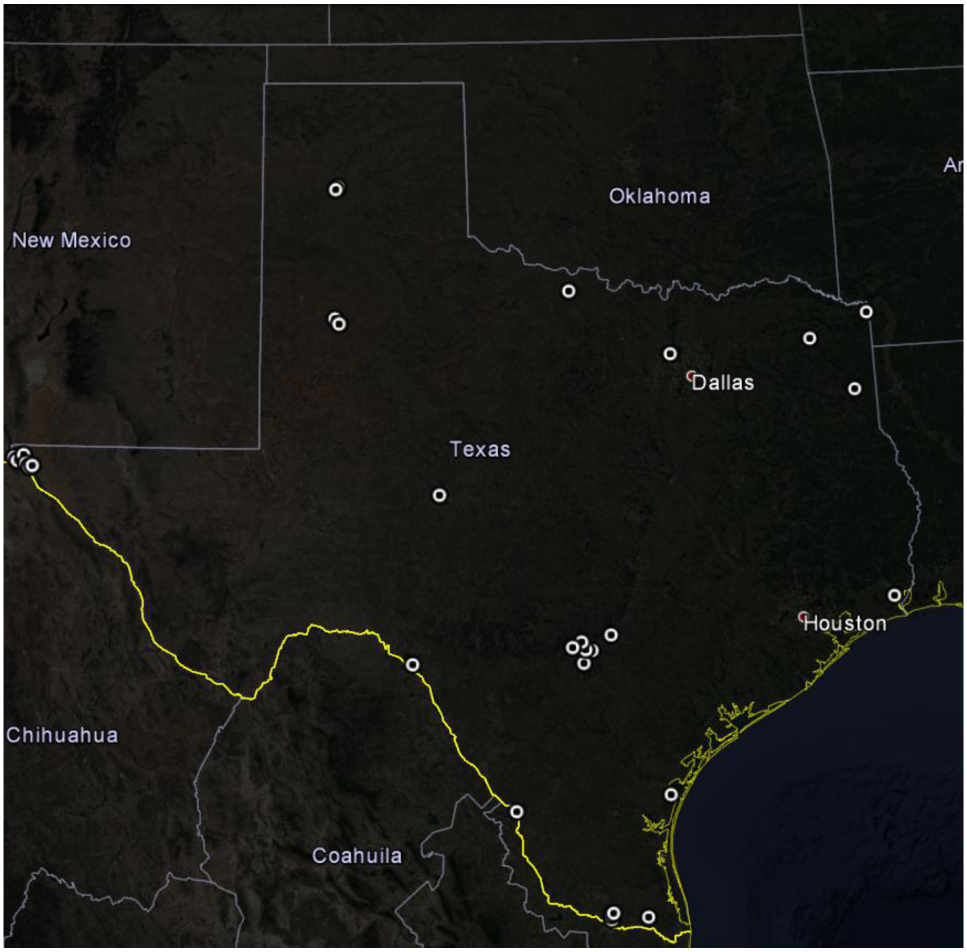


Figure 1.10: Locations of Company Owned Applebee's



Notes: Applebee's open any time between 2006 and 2013 are included.

FIGURE 1.11: Locations of Franchised Applebee's



Notes: Applebee's open any time between 2006 and 2013 are included.

Figure 1.12: Histogram of Store Revenues by Ownership Type for Q4 2006

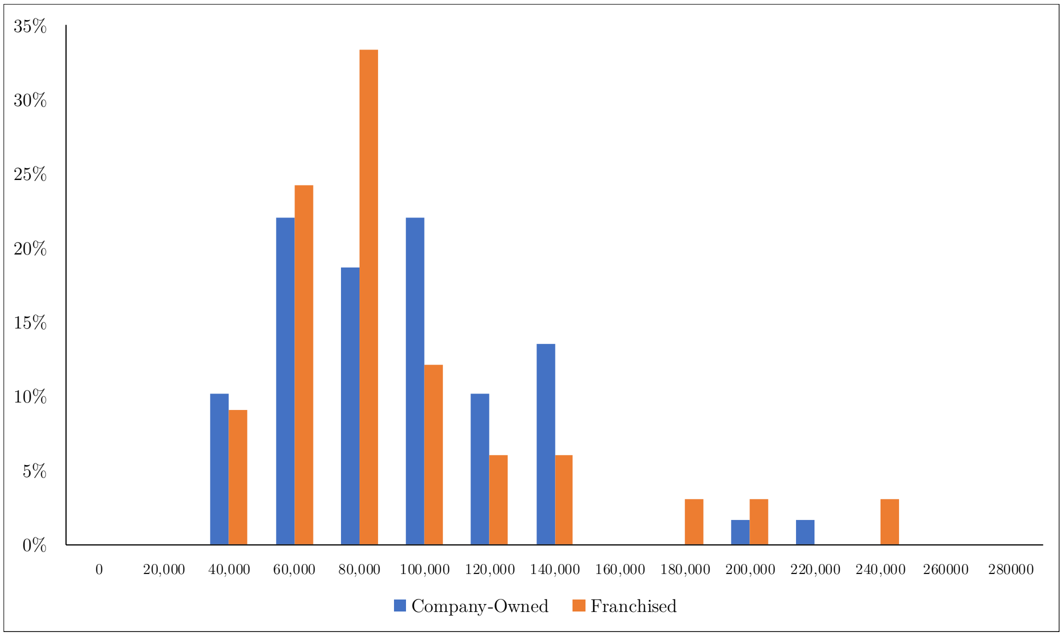
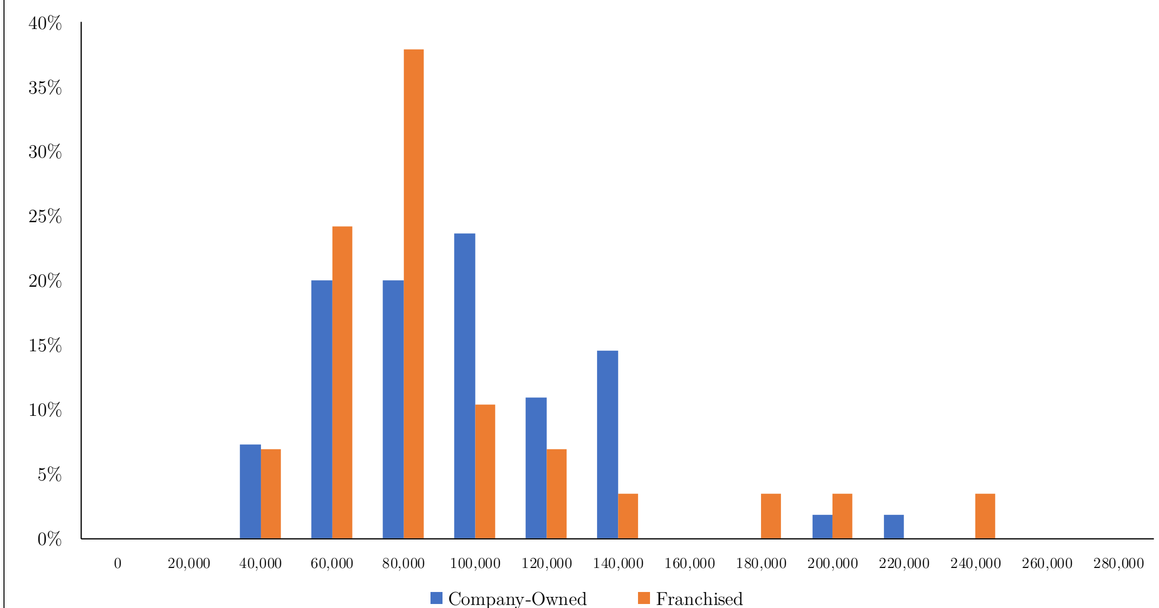


Figure 1.13: Histograms of Store Revenue for Q4 2006 and Q4 2013



Note: Histogram includes only stores which were still open in the fourth quarter of 2013.

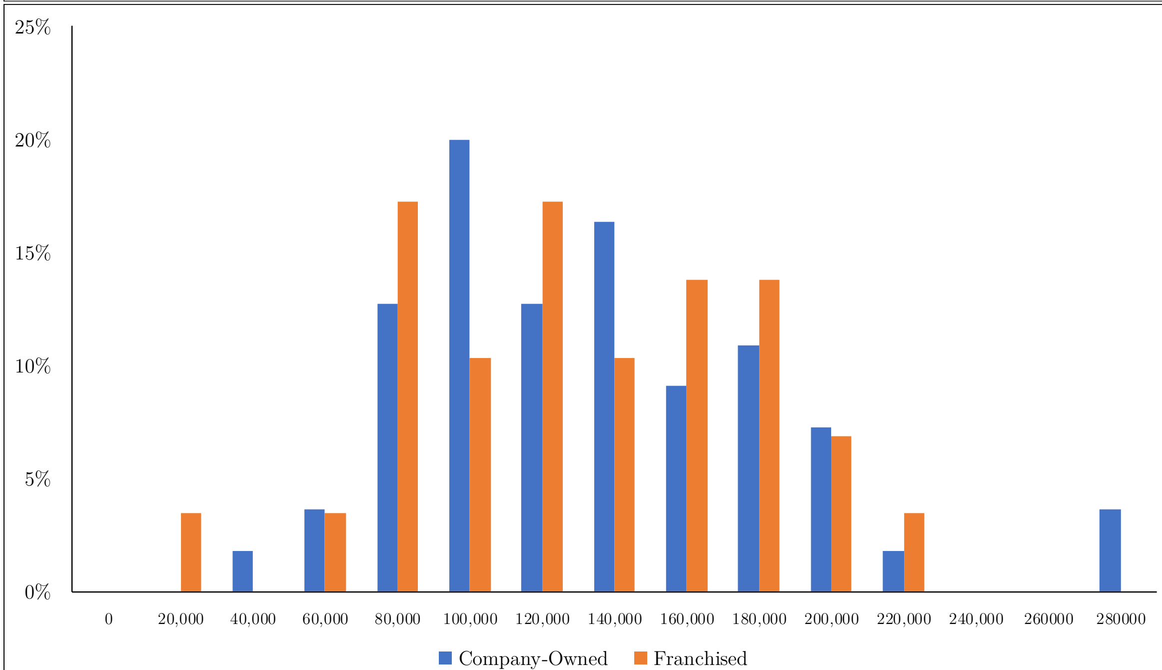
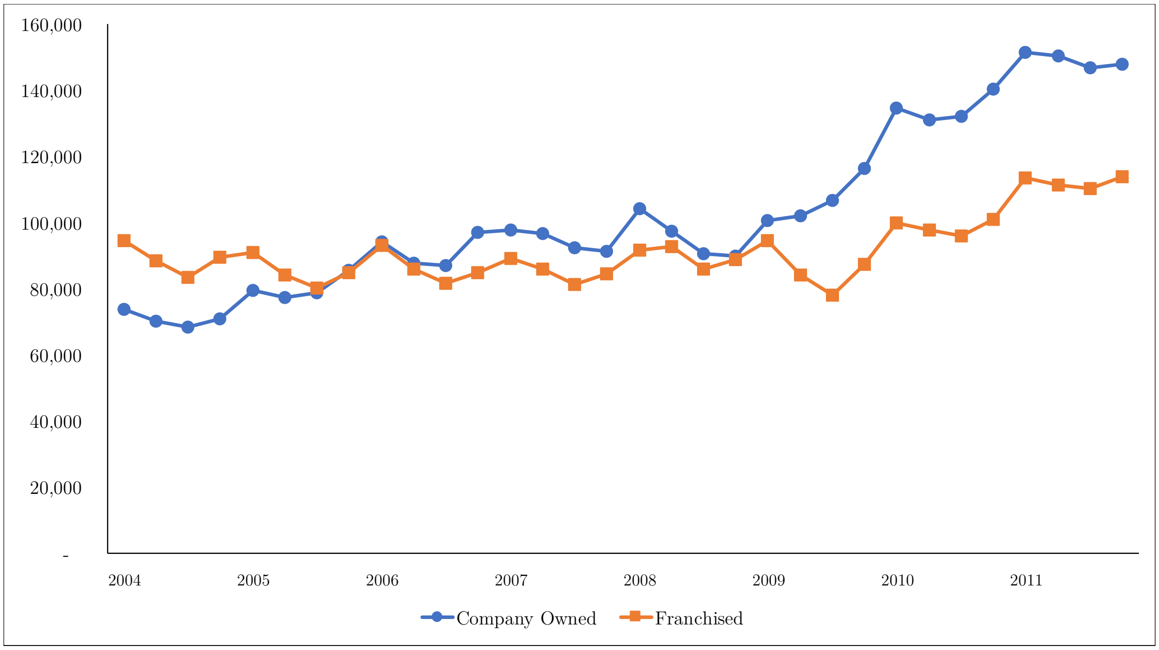


Figure 1.14: Average Yearly Sales by Ownership Type



Notes: Only stores which exist in all years from 2004 to 2011 are included. This includes 39 company-owned stores and 25 franchised stores.

CHAPTER 2

REDUCED FORM ANALYSIS

I begin my analysis by modeling the ownership decisions made by Applebee's prior to the 2007 corporate sale, namely whether a given store should be company-owned or franchised. I observe evidence of selection based on demographics; for example, Applebee's chose to own stores in higher income areas. I also find evidence that Applebee's chose to own stores in locations that were better due to factors that are unobservable to the econometrician. Next, I use a linear model with store level fixed effects to find evidence that franchising a store increases its revenue. For stores that change ownership, I find that franchising a store increases its revenue by 19 percent.

2.1 Empirical Analysis of the Franchisor's Ownership Decision

Here I investigate how Applebee's chose whether to own or franchise each store prior to 2008. I am most interested in investigating whether locations that, for reasons that are known to the franchisor and franchisee but unobserved by the econometrician, had higher revenue potential were less likely be franchised, as was predicted by the model in Section 1.3. I use a binomial logit regression where the dependent variable is equal to one if the store was initially franchised and zero otherwise. Only Applebee's stores that were opened before the IHOP sale are included in the regressions. For demographic variables, I use values from the beginning of 2008.

First, I examine whether there is selection based on observables. For simplicity, I initially consider only two observables: the logged population of the store's county and the share of the county's population that is non-Hispanic white.[26] This is subsequently

[26] I use county-level rather than zip code-level variables in these regressions due to data limitations; some of the demographic variables I use in different specifications of the models are only available on the county level.

referred to as “White”. As shown in Specification (1) of Table 2.1, regression results indicate that company-owned stores tended to be located in higher population areas and areas with fewer minorities. I expand the model to include two additional demographics. The first is the percentage of the county’s population that is employed at a full-service restaurant.[27] This is used as a proxy for how competitive the market is and is subsequently referred to as “Competition”. The second is the average per capita income for the store’s zip code. As shown in Specifications (2) and (3) of Table 2.1, I find that stores located in higher income areas and stores with fewer competitors were more likely to be company-owned. These coefficients are, in almost all specifications, all significantly different from zero, indicating that ownership selection was not random.

I next turn to evidence of selection based on unobservables. I do this using a modification of the “preprogram” regression described by Heckman and Hotz (1989). Specifically, I include average quarterly revenue for all periods after 2009 as an explanatory variable. If unobservable determinants of revenue were relevant in Applebee’s ownership decision, then, after all stores are franchised and all observable demographics are controlled for, stores that were initially company-owned should have significantly different revenues than those that were initially franchised. A more formal explanation can be found in Appendix A. As shown in Specifications (4) through (6) of Table 2.1, I find that stores that have higher post-2009 revenues were more likely to be company-owned prior to the 2008 IHOP sale. This supports the theory raised in Section 1.3 that Applebee’s chose to own stores in locations with better unobservables.

In Section 1.6, I found that the ownership of nearby stores was highly predictive of the ownership of a new store. In this section, I adapt my logit model in an attempt to account for this factor. Specifically, I estimate the model with the same explanatory variables as those in Table 2.1, but only include stores which existed at the beginning of

[27]The number of people in each county employed at a full-service restaurant is calculated by County Business Patterns.

my sample period.[28] This is an attempt to look at how ownership decisions were made before Applebee's had a large network of stores. One important caveat is that, at the start of my sample period, Applebee's had 51 stores open. Some of these stores are near each other, and it is likely that the ownership of nearby existing stores affected the opening of these stores. While results are generally similar to those presented in Table 2.1, there are some significant differences. The effect of population is smaller and, depending on the specification, not always significant. The coefficients on Competition and Income are no longer statistically significant. Perhaps most interestingly, the coefficient on Revenue is larger in absolute value. This suggests that, for these early stores, revenue potential was an especially large determinant of store ownership. Complete results are shown in Table 2.2.

As noted in Section 1.6, at the end of 2006, no counties had both company-owned and franchised stores. This suggests that Applebee's made an ownership decision once for each county. Because of this, the addition of multiple stores from the same county to the logit model may not improve the model. In Table 2.3, I consider each county to be a single observation. Results are directionally same to those presented in Table 2.1 and Table 2.2: the coefficients on Population, White, and Income are negative, while the coefficients on Competition are positive.

2.2 Initial Estimates of the Effect of Franchising

To show preliminary evidence of the effect of franchising on store revenues, I define r_{jt} as the alcohol sales for Applebee's store j during quarter t and use a fixed-effects linear model:

$$\log(r_{jt}) = f_{jt}\delta + x_{jt}\pi + \xi_j + \varepsilon_{jt}, \tag{2.6}$$

where f_{jt} is an indicator variable that is equal to 1 if store j is franchised at time t, x_{jt} contains observable variables, ξ_j is a store-level fixed effect, and ε_{jt} is an error term that

[28] In this case, that is the second quarter of 2001. While I have store ownership data for periods prior to that, this is the first quarter of data for which I have data on the Competition variable.

is independent across all observations. The parameters of the model are π and δ, with δ representing the effect of franchising. Because this is a log-linear model, δ represents the percentage increase in revenue that occurs when a store switches from company-owned to franchised. Initially, the only components of x_{jt} are yearly control variables.

I first consider a "naive regression" in which the Applebee's sale is not used as a source of variation. The fixed effects model is not appropriate in this context because any effect of franchising would be absorbed by the store-level fixed effect, so $\xi_j = 0$ for all j. The estimated value of δ represents the difference in sales for two stores that have the same values of x_{jt} but different ownership structures. I define this estimate of δ as δ^{NAIVE}, and I find that $\delta^{NAIVE} = .085$ with p < 0.01.

I next conduct a fixed effects regression by allowing ξ_j to take on different values; this allows me to control for location-level unobservables. For stores that are initially franchised, $f_{jt} = 1$ for all t, so any effect of franchising is captured in ξ_j. Identification of δ depends on the 2008 ownership change of Applebee's restaurants. For stores that experience this ownership change, δ is identified as the difference between revenues when the store is company-owned and revenues when the store is franchised, after controlling for the observable demographics in x_{jt}. I define the value of δ estimated by this model as δ^{FE}, and I find that $\delta^{FE} = .19$ with p < 0.01. Thus, the fixed effects regression predicts that franchising a store increases its revenue by 19 percent. The fact that $\delta^{FE} > \delta^{NAIVE}$ is consistent with the theory that locations with the best unobservables are more likely to be company-owned, which leads to the naive regression underestimating the franchise effect.

This fixed effects estimate does not include any control variables other than yearly fixed effects. If stores that were initially company-owned were located in counties that experienced significant population growth, and if this growth caused an increase in revenues relative to the revenues of stores that were always franchised, that revenue increase could be falsely attributed to a franchise effect. To address this, I estimate several additional specifications using different control variables. Additionally, because I do not observe when in 2008 the ownership changes occur, I separate the franchising effect into two components, one for 2008 and one for all subsequent years.

Table 2.4 shows the results from regressions using different demographics in a_{jt}. Because the model contains a store-level fixed effect, the components of a_{jt} are identified by demographics of a given county changing over time. So, a positive coefficient on "White" would reflect that revenue increases as a county's white population share increases. All specifications contain yearly and quarterly control variables. Specification (1) is the naive regression described in Section 2.2, and Specification (2) is the fixed effect regression described in Section 2.2. Specifications (3) through (5) continue to use fixed effects and use different combinations of parameters. For all, the estimated franchise effect is between 15 percent and 19 percent and is statistically significant. The 2008 effect is smaller (between 6 percent and 8 percent) and statistically insignificant in all specifications. The two demographics that were statistically significant in all specifications were population and race. As a county's population increases, average revenue for an Applebee's store in that county actually decreases. As a county's white population share increases, average revenue for an Applebee's store in that county decreases.

Trends

Table 2.10 introduces trends to the model. To address the possibility that the stores that were initially company-owned were experiencing rapid revenue growth before and after the ownership change, and that the observed revenue increase was unrelated to any franchising effect, I use two different types of trends. The first are store level trends, used in Specifications (1) through (3). In these specifications, each store is given its own time trend. As a result, the estimated franchise effects are smaller (between 3 percent and 10 percent) and statistically insignificant. The second type of trend is an ownership level trend. Here, stores that were initially company-owned are all given the same trend. I refer to this as "COS trend" and show the coefficients in the table.[29] Here, the estimated franchise effects are between 7 percent and 16 percent, which is closer to the no-trend estimates. Statistical significance depends on the demographic control variables used.

It is notable that in most specifications the coefficient on the trend is statistically insignificant; this suggests that there is not actually an upward trend and that the trend variable is simply causing the franchise effect to be split between the "Franchise effect" variable and the "COS trend" variable. Also supporting this interpretation is the fact that the addition of a trend gives only a negligible improvement to the fit of the model.

In Table 2.11, I show several additional specifications using various combinations of demographic variables. This includes one new demographic: "Age 20-35", which is equal to the share of the population in the county where the store is located that is between 20-35. Specifications (1) through (3) do not have a trend; specifications (4) through (6) include the "COS trend" variable. Results are directionally similar to those discussed above; with no trends included, the estimated franchise effect is between 13 percent and 15 percent and is statistically significant. With an ownership level trend included, the franchise effect is between nine percent and 10 percent, and its statistical significance depends on the choice of demographic variables included in the regression.

Effect of IHOP's Ownership

Following the acquisition of Applebee's, IHOP made changes to its menus, suppliers, and advertising strategies. In a 2008 interview, IHOP's CEO stated her intention to focus on increasing Applebee's alcohol sales by adding televisions to bar areas and emphasizing the variety of available beverages (Horovitz, 2008). The results of the above regressions allow me to gain preliminary evidence regarding whether IHOP's ownership change and resulting change in business practices had an impact on the revenues of all Applebee's stores. Specifically, yearly fixed effects are included in each regression to account for factors that affect the performance of all Applebee's stores. Figure 2.1 shows a graph

[29] Any trend that affected all Applebee's stores is accounted for in the yearly control variables.

of the estimated parameters for the yearly fixed effects from Specification (5) of Table 2.4. The estimated fixed effects from 2010 through 2013 are substantially higher than the estimated fixed effects from 2004 through 2009. However, I cannot identify whether this is due to a change in macroeconomic conditions or due to policies implemented at the chainwide level. One piece of evidence supporting the theory that IHOP's ownership increased Applebee's revenues can be found in Figure 1.3, which shows average per-store revenues for each chain over time; it is likely that any macroeconomic condition that positively affected Applebee's would have also had an effect on other chain restaurants. However, Buffalo Wild Wings and Chili's do not show a revenue increase after 2009. T.G.I. Friday's does have a revenue increase, but it is smaller than the increase experienced by Applebee's.

Variance of Franchise Effect

I next investigate how the franchise effect varies by store. To do this, I estimate a model which has the same explanatory variables as Specification (4) in Table 2.4. However, I separately estimate a different franchise effect for each store. While the average store experienced a franchise effect of 12.7%, a quarter of the stores have a franchise effect that is negative, and a quarter of the stores have a franchise effect that is greater than 43%.[30] A histogram of all estimated franchise effects is shown in Figure 2.2.

I next investigate whether the magnitude of the franchise effect is correlated with store-level unobservables. It is likely that, if the franchisor can determine what the magnitude of the franchise effect for a given store would be, stores with large franchise effects will tend to be franchisee-owned. This predicts that stores which are both low-revenue (after franchising) and company-owned will have a small benefit from franchising; if the store had a large benefit from franchising *and* was in a poor location, it would

[30]It is important to note that a negative franchise effect does not necessarily mean that store revenues were decreasing; it just means that the store did worse than a comparable store that was already franchised would have been expected to do.

have initially been franchised. However, as shown in Figure 2.3, there is essentially no relationship between a company-owned store's 2006 revenue and the magnitude of its franchise effect.

Further Discussion of Ownership Selection

It is worthwhile to compare the results shown in Tables 2.4 and 2.10 with the logit model results shown in Table 2.1, Table 2.2, and Table 2.3. For example, locations with more competition tend to have lower revenues. Locations with more competition were also more likely to be franchised.[31] This supports the hypothesis that Applebee's preferred to franchise stores with lower revenue potential. Similarly, locations with low incomes tend to have lower revenues, so it is unsurprising that Applebee's preferred to franchise stores in low-income areas. However, Applebee's preferred to own stores in counties with fewer minorities, even though those counties tend to have lower revenues, and Applebee's preferred to own stores in counties that had higher populations, even though they tend to have lower revenues.

It is possible that the reason Applebee's preferred to own stores in high-population counties is related to the local expertise hypothesis of why firms franchise. It may be the case that, for large cities like Dallas, Applebee's management thought that they had a good understanding of the local market or could easily obtain relevant market research, while for a small town they believed that a local expert would be better able to deal with the intricacies of the market. This is a potential area for further research.

2.3 Comparison with Buffalo Wild Wings

As of the first quarter of 2013, Buffalo Wild Wings had 40 company-owned restaurants and 42 franchised restaurants in Texas. No Buffalo Wild Wings changed franchise status during my sample period, so I cannot identify the effect of franchising on alcohol revenues. I am, however, able to see if the findings from the analysis of Applebee's also hold for

[31] One important caveat for these comparisons is that for the linear model, because there are store-level fixed effects, coefficients are identified by changes in demographics for a given county, not by comparing demographics between counties.

another chain. Like Applebee's, many of Buffalo Wild Wings' company-owned stores are located in Houston or Dallas, while the franchised stores tend to be located in smaller markets that contain only one Buffalo Wild Wings. Figures 2.4 and 2.5 show the locations of company-owned and franchised Buffalo Wild Wings stores in Texas.

I first use a logit model to predict ownership of Buffalo Wild Wings stores, using the same demographic predictor variables as were used to predict ownership of Applebee's stores. As was the case with Applebee's, company-owned Buffalo Wild Wings stores tend to be located in counties with higher populations, higher incomes, fewer minorities, and less competition. Complete results are shown in Table 2.5. Specifications (4) through (6) include revenue as a predictor. The results find that higher revenues are correlated with more franchisee ownership. Because there is no ownership change in Buffalo Wild Wings stores, this cannot be used to estimate unobservables as was done in Section 2.1.

I next use linear regressions to model store revenues. The first set of regressions is intended to show how demographics affect store revenues. The regressions use county-level demographics, store-level fixed effects, and yearly and quarterly controls to predict logged quarterly revenues. Note that, as was the case in the Applebee's analysis, because store-level fixed effects are used, demographic effects are identified by changes in demographics over time at a given store. Results are shown in Table 2.6. As a county's population increases, its income increases, or its share of minorities increases, revenues of Buffalo Wild Wings stores in that county tend to increase. As a county's restaurant industry gets more competitive, revenues of Buffalo Wild Wings stores in that county tend to decrease. Most of these results are directionally similar to the results of the regression using Applebee's data shown in Table 2.4. The only differences are that, with Applebee's data, the coefficients on Competition and Income were not statistically significant, and the coefficient on Income was negative.

Finally, I add several binary variables to the regressions discussed above. The first is equal to one if the store is franchised and is referred to as "Franchised". The second is equal to one if the store is within five miles of an Applebee's that was initially company-owned; Figure 2.6 shows the locations of these stores. The third is equal to one if the store is within five miles of an Applebee's that was open prior to the IHOP sale and was initially franchised; Figure 2.7 shows the locations of these stores. Because these variables do not change for a given store over time, fixed effects are no longer appropriate and are not used. The results are shown in Table 2.7. Specifications (1) through (3) use the same demographic variables as the three specifications in Table 2.6. Specification (4) excludes all demographics.

In all specifications, the coefficient on Franchised is positive and indicates that franchised Buffalo Wild Wings stores earn between 11 percent and 24 percent more than company-owned stores. I cannot determine if this is because franchising increases store revenue or because franchised stores are at locations with better unobservables. I turn next to the coefficients on the binary variables that indicate proximity to an Applebee's. The results shown in Specifications (1) and (2) of Table 2.4 and discussed in Section 2.2 suggest that company-owned Applebee's stores were in locations that are unobservably better than the locations of franchised Applebee's stores. It may be that Buffalo Wild Wings stores located near company-owned Applebee's stores share these characteristics and, therefore, earn higher revenues. This would manifest itself in a positive coefficient on the variable that indicates proximity to a company-owned Applebee's store. However, the coefficient on this variable is negative and significant, while the coefficient on the variable that indicates proximity to an always-franchised Applebee's store is positive. This indicates that Buffalo Wild Wings stores that are located near company-owned Applebee's stores (which, according to previous results, have "good" unobservables) have "bad" unobservables.

I next investigate some possible reasons for this finding. For example, it may be that five miles is a far enough distance that unobservables are not likely to be correlated; it may be that unobservably "good" locations are not good because they are in good neighborhoods but because they have chosen to be at the right place within a neighborhood. To account for this, I rerun the regressions but change the distance requirement from five miles to two miles. The results are essentially unchanged, as shown in Table 2.8. I also run a set of regressions that only include data after 2009; this ensures that all Applebee's stores are franchised and, thus, differences in performance for Buffalo Wild Wings stores are not due to some stores competing against franchised stores and others competing against company-owned stores. Results are shown in Table 2.9 and, again, are essentially unchanged from the results of baseline model.

While it is not clear why Buffalo Wild Wings stores located near originally company-owned Applebee's stores perform worse than those located near originally franchised Applebee's stores, one explanation relates to the fact that all of the Buffalo Wild Wings stores that are located near company-owned Applebee's stores are located in the eastern half of the state, mostly in Dallas, while most of the Buffalo Wild Wings stores that are located near franchised Applebee's stores are located in other parts of the state. It may be that people in the eastern part of Texas have an especially strong preference for Applebee's relative to Buffalo Wild Wings. This is would be an example of unobserved heterogeneity among consumers; a more rigorous comparison of the two chains would need to account for this potential heterogeneity.

2.4 Conclusion

In this chapter, I first found that Applebee's chose whether to own or franchise a given restaurant based on a variety of factors, only some of which were observed by me. I found that, as expected, stores that were initially owned by Applebee's tended to have better unobservables, indicating the importance of controlling for endogeneity of ownership selection when estimating the effect of franchising on store performance. I next used a fixed effects linear regression to estimate the effect of franchising on store performance. I found franchising a store increased its alcohol revenue. The magnitude varied based on the model used; for models without time trends, the estimated effect was between 15% and 19%. For models with time trends, the estimated effect was between 4% and 11% and was not always statistically significant. I also found that, as expected, a regression that did not take advantage of the ownership changes underestimated the magnitude of the franchise effect.

Throughout this section, I used the term "unobservables" to include all factors that were not observed by me but are potentially known by the franchisor. While my analysis includes only a small set of demographics, it is likely that no available data set would contain every piece of information relevant to store sales that is available to the franchisor. Thus, while adding additional demographics and other observables may increase the precision of my estimates, it is likely that the most important results of this section – that locations with the best unobservables tend to be company owned and that failing to account for these unobservables can lead to an underestimate of the franchise effect – would be unchanged.

Table 2.1: Logit Model Predicting if a Store Will be Franchised

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Population	-1.346***	-1.553***	-0.779	-1.418***	-1.615***	-0.701
	(0.359)	(0.400)	(0.492)	0.372	(0.412)	(0.525)
White	-13.561***	-14.56***	-10.83***	-14.173***	-15.441***	-11.23***
	(3.314)	(3.532)	(3.853)	(3.361)	(3.702)	(3.939)
Competition		157.9*	215.1**		145.831*	187.4**
		(81.02)	(88.33)		(84.757)	(90.79)
Income			-1.631**			-1.714**
			(0.647)			(0.691)
Revenue				-1.77e-05**	-1.75e-5**	-2.17e-05**
				(7.81e-06)	(8.12e-06)	(9.57e-06)
Constant	23.818***	24.47***	18.00**	26.397***	27.781***	20.31***
	(6.198)	(6.497)	(7.086)	(6.649)	(7.01)	(7.406)
Observations	90	90	90	87	87	87

Notes: A positive coefficient indicates that an increase in the value of the variable will result in an increase in the likelihood that the store is franchised. "Population", "White", "Competition", and "Income" are demographics for the county where the store is located; "Population" is the log of the county's population, "White" is the population share that is non-Hispanic white, "Competition" is the share of population employed at a full-service restaurant, and "Income" is the average per-capita income. "Revenue" is the average post-2009 revenue of the store. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.2: Logit Model Predicting if a Store Will be Franchised - Only Stores Open in Q2 2001 Included

Variables	(1)	(2)	(3)	(4)	(5)	(6)	
Population	-0.815**	-0.884**	-0.470	-0.885	-0.641	-0.187	
	(0.389)	(0.428)	(0.594)	(0.560)	(0.644)	(0.817)	
White	-9.610***	-9.801***	-7.360**	-15.76***	-15.62***	-13.19**	
	(2.855)	(2.897)	(3.717)	(4.669)	(4.682)	(5.349)	
Competition		37.27	95.51		-107.0	-52.76	
		(95.06)	(112.8)		(144.8)	(165.3)	
Income			-1.257			-1.390	
			(1.246)			(1.638)	
Revenue				-3.77e-05**	-4.20e-05**	-4.22e-05**	1
				(1.54e-05)	(1.72e-05)	(1.79e-05)	
Constant	15.28**	15.72**	11.72	24.12**	23.02**	18.94*	
	(6.215)	(6.303)	(7.424)	(9.373)	(9.479)	(10.18)	
Observations	56	56	56	51	51	51	

Notes: A positive coefficient indicates that an increase in the value of the variable will result in an increase in the likelihood that the store is franchised. “Population”, “White”, “Competition”, and “Income” are demographics for the county where the store is located; “Population” is the log of the county’s population, “White” is the population share that is non-Hispanic white, “Competition” is the share of population employed at a full-service restaurant, and “Income” is the average per-capita income. “Revenue” is the average post-2009 revenue of the store. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.3: Logit Model Predicting the Initial Franchise Status of Applebee's Stores in Each County

Variables	(1)	(2)	(3)
Population	-2.30e-06*	-2.88e-06**	-2.04e-06
	(1.18e-06)	(1.37e-06)	(1.47e-06)
White	-10.40***	-10.88***	-9.412**
	(3.620)	(3.704)	(4.109)
Competition		139.8	193.8*
		(89.11)	(102.5)
Income			-1.318
			(0.937)
Constant	6.509***	4.923*	7.395**
	(2.469)	(2.578)	(3.435)
Observations	47	47	47

Notes: A positive coefficient indicates that an increase in the value of the variable will result in an increase in the likelihood that the store is franchised. "Population", "White", "Competition", and "Income" are demographics for the county where the store is located; "Population" is the log of the county's population, "White" is the population share that is non-Hispanic white, "Competition" is the share of population employed at a full-service restaurant, and "Income" is the average per-capita income. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.4: Estimated Effect of Franchising: Fixed Effects Model

Variables	(1)	(2)	(3)	(4)	(5)
Franchise effect	0.0852***	0.191***	0.151***	0.155***	0.153***
	(0.0240)	(0.0430)	(0.0480)	(0.0484)	(0.0478)
2008 effect			0.0809*	0.0734*	0.0697
			(0.0424)	(0.0427)	(0.0423)
Population			-1.038**	-0.930**	-0.891**
			(0.416)	(0.404)	(0.373)
White			-5.862***	-6.111***	-6.057***
			(1.846)	(1.807)	(1.829)
Competition				-15.25	-15.04
				(9.681)	(9.818)
Income					0.0548
					(0.0941)
Fixed effects	No	Yes	Yes	Yes	Yes
Constant			27.61***	26.55***	25.84***
			(5.875)	(5.703)	(5.259)
Observations			3,317	3,223	3,223
R-squared			0.560	0.565	0.565

Notes: The dependent variable is logged quarterly store-level alcohol sales. "Population", "White", "Competition", and "Income" are demographics for the county where the store is located; "Population" is the log of the county's population, "White" is the population share that is non-Hispanic white, "Competition" is the share of population employed at a full-service restaurant, and "Income" is the average per-capita income. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Logit Model Predicting if a Buffalo Wild Wings Store Will be Franchised

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Population	-1.557***	-1.835***	-1.601***	-1.481***	-1.875***	-1.123**
	(0.362)	(0.399)	(0.412)	(0.365)	(0.431)	(0.466)
White	-9.922***	-10.97***	-10.11***	-9.825***	-11.63***	-8.849***
	(2.770)	(2.761)	(2.985)	(2.779)	(2.882)	(3.409)
Competition		233.2**	256.8**		278.0***	338.3***
		(98.51)	(100.3)		(102.0)	(110.8)
Income			-0.609*			-1.442***
			(0.324)			(0.540)
Revenue				9.08e-06	1.37e-05**	1.61e-05***
				(5.60e-06)	(6.63e-06)	(6.13e-06)
Constant	25.69***	26.04***	24.90***	22.90***	23.60***	17.25**
	(6.023)	(6.022)	(6.299)	(6.132)	(6.259)	(7.274)
Observations	82	82	82	82	82	82

Notes: A positive coefficient indicates that an increase in the value of the variable will result in an increase in the likelihood that the store is franchised. “Population”, “White”, “Competition”, and “Income” are demographics for the county where the store is located; “Population” is the log of the county’s population, “White” is the population share that is non-Hispanic white, “Competition” is the share of population employed at a full-service restaurant, and “Income” is the average per-capita income. “Revenue” is the revenue of the store in the first quarter of 2013. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.6: Impact of Demographics on Buffalo Wild Wings Store Revenue

Variables	(1)	(2)	(3)
Population	0.602***	0.618***	0.622***
	(0.0567)	(0.0591)	(0.0590)
White	-5.770***	-5.938***	-5.085***
	(0.745)	(0.775)	(0.811)
Competition		-11.22*	-12.91**
		(6.408)	(6.408)
Income			0.0770***
			(0.0222)
Constant	7.122***	7.079***	5.639***
	(0.911)	(0.926)	(0.926)
Observations	2,135	2,047	2,047
R-squared	0.188	0.191	0.196

Notes: The dependent variable is logged quarterly store-level alcohol sales. All models include store level fixed effects and yearly and quarterly control variables. “Population”, “White” , “Competition”, and “Income” are demographics for the county where the store is located; “Population” is the log of the county’s population, “White” is the population share that is non-Hispanic white, “Competition” is the share of population employed at a full-service restaurant, and “Income” is the average per-capita income. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.7: Using Nearby Applebee's Store Ownership to Predict Buffalo Wild Wings Store Revenue

Variables	(1)	(2)	(3)	(4)
Population	0.0483***	0.0705***	0.0194*	
	(0.00802)	(0.00866)	(0.00990)	
White	0.445***	0.592***	0.326***	
	(0.0438)	(0.0478)	(0.0554)	
Competition		-14.41***	-22.48***	
		(2.276)	(2.398)	
Income			0.150***	
			(0.0122)	
Franchised	0.186***	0.215***	0.238***	0.112***
	(0.0175)	(0.0185)	(0.0185)	(0.0158)
Within 5 of APL C	-0.250***	-0.260***	-0.229***	-0.203***
	-0.0162	-0.0164	-0.0158	(0.0145)
Within 5 of APL F	0.113***	0.117***	0.220***	0.0731***
	(0.0219)	(0.0220)	(0.0199)	(0.0204)
Constant	11.59***	11.27***	11.72***	12.26***
	(0.138)	(0.143)	(0.151)	(0.0255)
Observations	2,126	2,038	2,038	2,550
R-squared	0.268	0.284	0.347	0.212

Notes: The dependent variable is logged quarterly store-level alcohol sales. All models include yearly and quarterly control variables. "Within 5 of APL C" is equal to 1 if the store is within five miles of an Applebee's that was originally company-owned. "Within 5 of APL F" is equal to 1 if the store is within five miles of an Applebee's that was open prior to 2007. "Population", "White", "Competition", and "Income" are demographics for the county where the store is located; "Population" is the log of the county's population, "White" is the population share that is non-Hispanic white, "Competition" is the share of population employed at a full-service restaurant, and "Income" is the average per-capita income. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.8: Prediction of Buffalo Wild Wings Store Revenue - Two Mile Maximum Distance

Variables	(1)	(2)	(3)	(4)
Population	0.0415***	0.0604***	0.0224**	
	(0.00901)	(0.00998)	(0.0112)	
White	0.330***	0.444***	0.211***	
	(0.0489)	(0.0564)	(0.0655)	
Competition		-11.25***	-18.37***	
		(2.624)	(2.823)	
Income			0.120***	
			(0.0144)	
Franchised	0.227***	0.253***	0.293***	0.154***
	(0.0169)	(0.0182)	(0.0191)	(0.0142)
Within 2 of APL C	-0.186***	-0.186***	-0.155***	-0.153***
	(0.0163)	(0.0164)	(0.0156)	(0.0138)
Within 2 of APL F	0.118***	0.132***	0.191***	0.0747***
	(0.0252)	(0.0259)	(0.0247)	(0.0216)
Constant	11.74***	11.43***	11.77***	12.20***
	(0.154)	(0.159)	(0.167)	(0.0246)
Observations	2,126	2,038	2,038	2,550
R-squared	0.206	0.217	0.260	0.166

Notes: The dependent variable is logged quarterly store-level alcohol sales. All models include yearly and quarterly control variables. “Within 5 of APL C” is equal to 1 if the store is within two miles of an Applebee’s that was originally company-owned. “Within 5 of APL F” is equal to 1 if the store is within two miles of an Applebee’s that was open prior to 2007. “Population”, “White”, “Competition”, and “Income” are demographics for the county where the store is located; “Population” is the log of the county’s population, “White” is the population share that is non-Hispanic white, “Competition” is the share of population employed at a full-service restaurant, and “Income” is the average per-capita income. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.9: Prediction of Buffalo Wild Wings Store Revenue - 2009 and Later

Variables	(1)	(2)	(3)	(4)
Population	0.0310***	0.0508***	0.00382	
	(0.00959)	(0.0107)	(0.0115)	
White	0.485***	0.610***	0.352***	
	(0.0522)	(0.0584)	(0.0646)	
Competition		-10.96***	-19.59***	
		(2.630)	(2.740)	
Income			0.150***	
			(0.0139)	
Franchised	0.139***	0.172***	0.195***	0.0837***
	(0.0211)	(0.0237)	(0.0229)	(0.0190)
Within 5 of APL C	-0.249***	-0.259***	-0.225***	-0.187***
	(0.0200)	(0.0204)	(0.0194)	(0.0168)
Within 5 of APL F	0.126***	0.123***	0.237***	0.0851***
	(0.0274)	(0.0281)	(0.0238)	(0.0253)
Constant	11.51***	11.40***	11.65***	12.20***
	(0.159)	(0.163)	(0.161)	(0.0240)
Observations	1,369	1,287	1,287	1,793
R-squared	0.251	0.266	0.347	0.178

Notes: The dependent variable is logged quarterly store-level alcohol sales. All models include yearly and quarterly control variables. “Population”, “White”, “Competition”, and “Income” are demographics for the county where the store is located; “Population” is the log of the county’s population, “White” is the population share that is non-Hispanic white, “Competition” is the share of population employed at a full-service restaurant, and “Income” is the average per-capita income. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.10: Estimated Effect of Franchising: Comparison of Time Trends

Time Trend:	Store Level Trends			Ownership Level Trend		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Franchise effect	0.0812	0.0413	0.0539	0.108**	0.0773	0.0850
	(0.0600)	(0.0586)	(0.0639)	(0.0492)	(0.0521)	(0.0541)
2008 effect	-0.00344	-0.0317	-0.0284	0.0605	0.0358	0.0375
	(0.0484)	(0.0479)	(0.0479)	(0.0451)	(0.0447)	(0.0446)
Population	2.218*	2.000	1.917	-1.054**	-0.954**	-0.925**
	(1.177)	(1.205)	(1.209)	(0.419)	(0.404)	(0.372)
White	-6.241	-7.589	-7.944	-5.688***	-5.798***	-5.797***
	(5.397)	(5.696)	(5.751)	(1.852)	(1.821)	(1.831)
Competition		-20.69**	-21.71**		-15.96	-15.74
		(10.41)	(10.53)		(9.786)	(9.849)
Income			0.0498			0.0364
			(0.0623)			(0.0956)
COS trend				0.00215	0.00393	0.00350
				(0.00215)	(0.00241)	(0.00218)
Constant	-14.32	-10.53	-9.375	27.71***	26.67***	26.18***
	(17.02)	(17.67)	(17.74)	(5.873)	(5.663)	(5.234)
Observations	3,317	3,223	3,223	3,317	3,223	3,223
R-squared	0.726	0.730	0.730	0.561	0.566	0.566

Notes: All specifications use store-level fixed effects. “Population”, “White” , “Competition”, and “Income” are demographics for the county where the store is located; “Population” is the log of the county’s population, “White” is the population share that is non-Hispanic white, “Competition” is the share of population employed at a full-service restaurant, and “Income” is the average per-capita income. “COS trend” is a linear time trend that applies to all stores that were initially company-owned. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.11: Estimated Effect of Franchising: Alternative Specifications

	No Trends			Ownership-Level Trend		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Fra. effect	0.136***	0.138***	0.149***	0.0980*	0.0980*	0.0864
	(0.0459)	(0.0470)	(0.0471)	(0.0550)	(0.0550)	(0.0523)
2008 effect	0.0641	0.0685	0.0775*	0.0461	0.0461	0.0432
	(0.0413)	(0.0420)	(0.0419)	(0.0453)	(0.0453)	(0.0451)
Population	-1.261***	-1.296***	-0.999**	-1.257***	-1.282***	-1.018***
	(0.366)	(0.393)	(0.383)	(0.365)	(0.387)	(0.383)
White	-6.019***	-6.084***	-5.802***	-5.874***	-5.872***	-5.679***
	(1.792)	(1.769)	(1.863)	(1.800)	(1.792)	(1.861)
Competition	-13.23	-13.53		-13.75	-14.16	
	(9.397)	(9.265)		(9.421)	(9.359)	
Income	0.0639		0.0518	0.0528		0.0432
	(0.0945)		(0.0971)	(0.0960)		(0.0983)
Age 20-35	-5.175**	-5.027*		-4.837*	-4.606*	
	(2.595)	(2.575)		(2.741)	(2.706)	
COS trend				0.00199	0.00269	0.00164
				(0.00217)	(0.00244)	(0.00189)
Constant	31.74***	32.40***	26.92***	31.55***	31.99***	27.12***
	(5.341)	(5.698)	(5.404)	(5.339)	(5.610)	(5.398)
Observations	3,223	3,223	3,317	3,223	3,223	3,317
R-squared	0.569	0.568	0.561	0.569	0.569	0.561

Notes: All specifications use store-level fixed effects. "Population", "White" , "Competition", "Income", and "Age 20-35" are demographics for the county where the store is located; "Population" is the log of the county's population, "White" is the population share that is non-Hispanic white, "Competition" is the share of population employed at a full-service restaurant, "Income" is the average per-capita income, and "Age 20-35" is the population share that is between the ages of 20 and 35. "COS trend" is a linear time trend that applies to all stores that were initially company-owned. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

FIGURE 2.1: Fixed Effects Regression Estimate of Yearly Control Variables

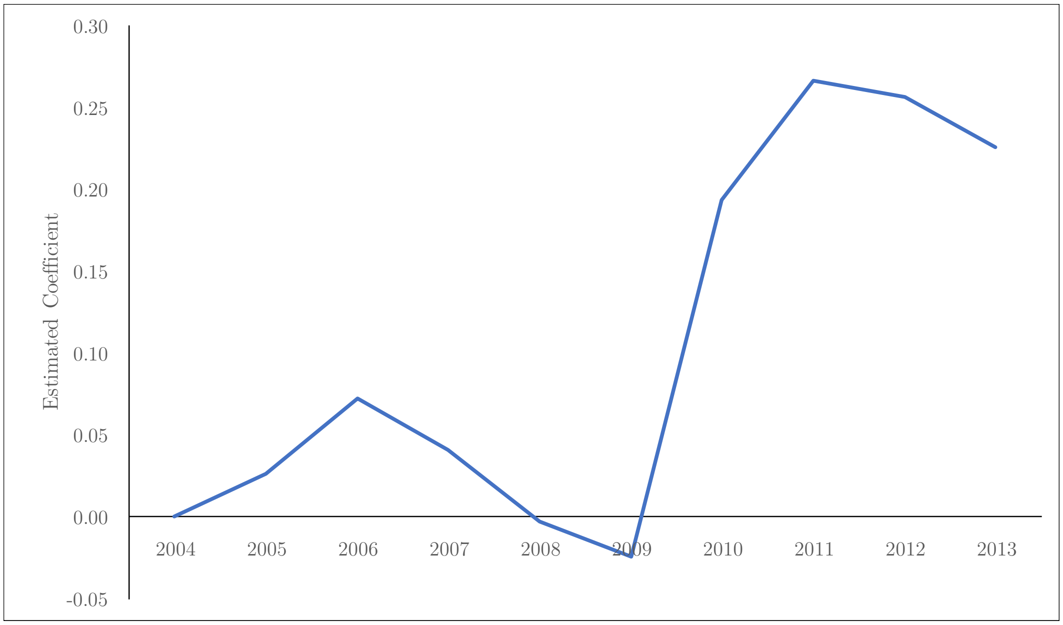
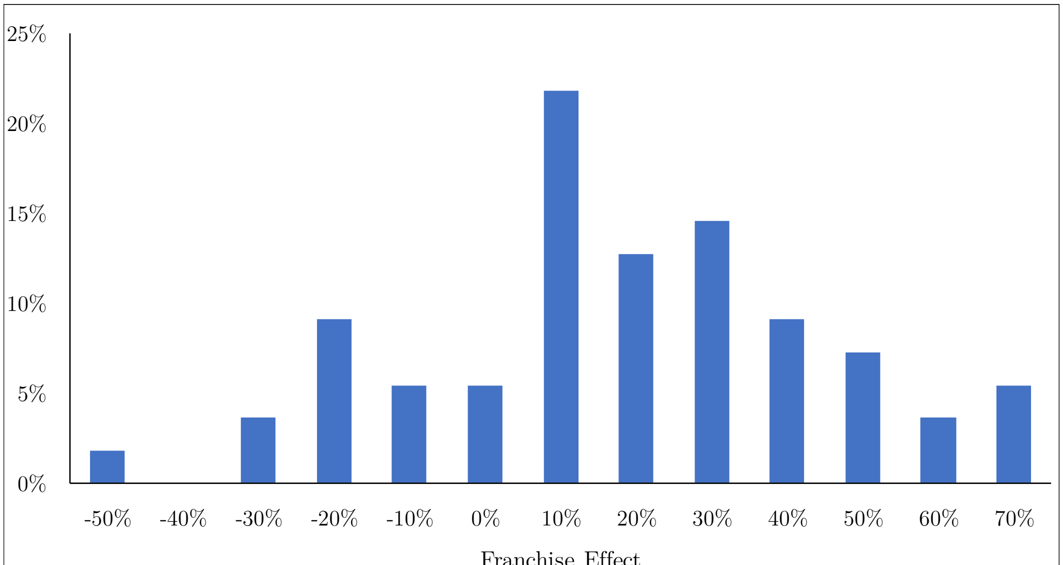
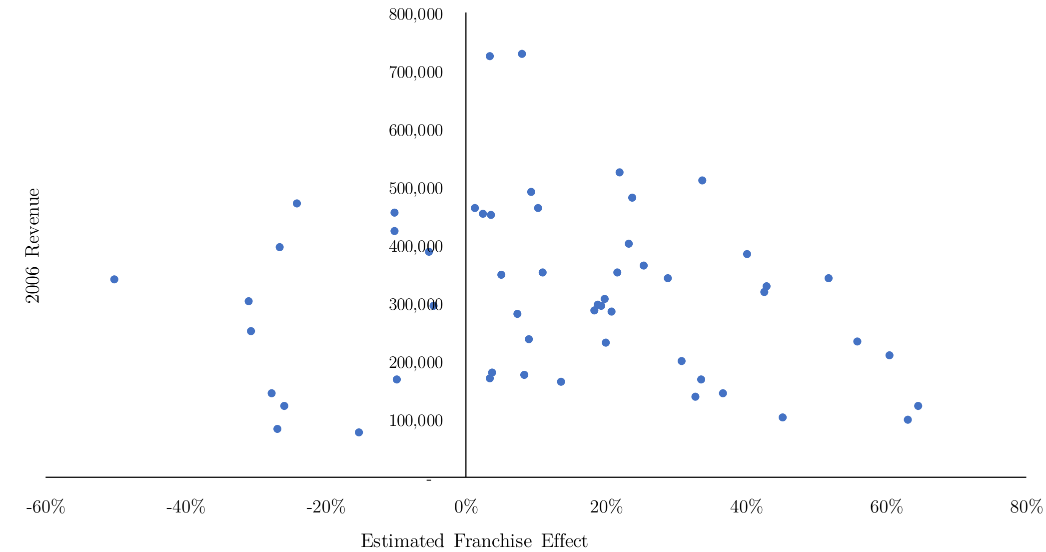


FIGURE 2.2: Histogram of Estimated Franchise Effects by Store



Notes: Estimates are taken from a fixed effects regression which includes control variables used in Specification (4) in

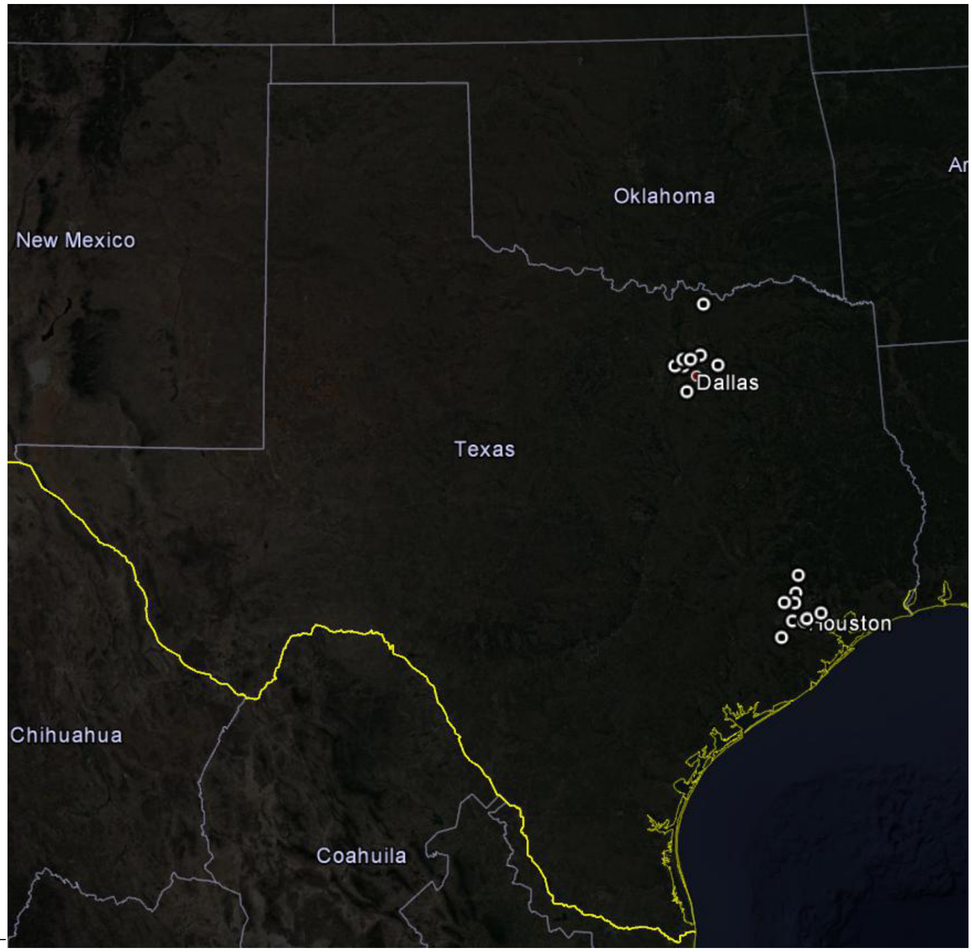
Figure 2.3: Relationship Between Estimated Store-Level Franchise Effect and 2006 Revenue



Notes: Franchise effect estimates are taken from a fixed effects regression which includes control variables used in Specification (4) in Table 2.4. A separate franchise effect is estimated for each store.

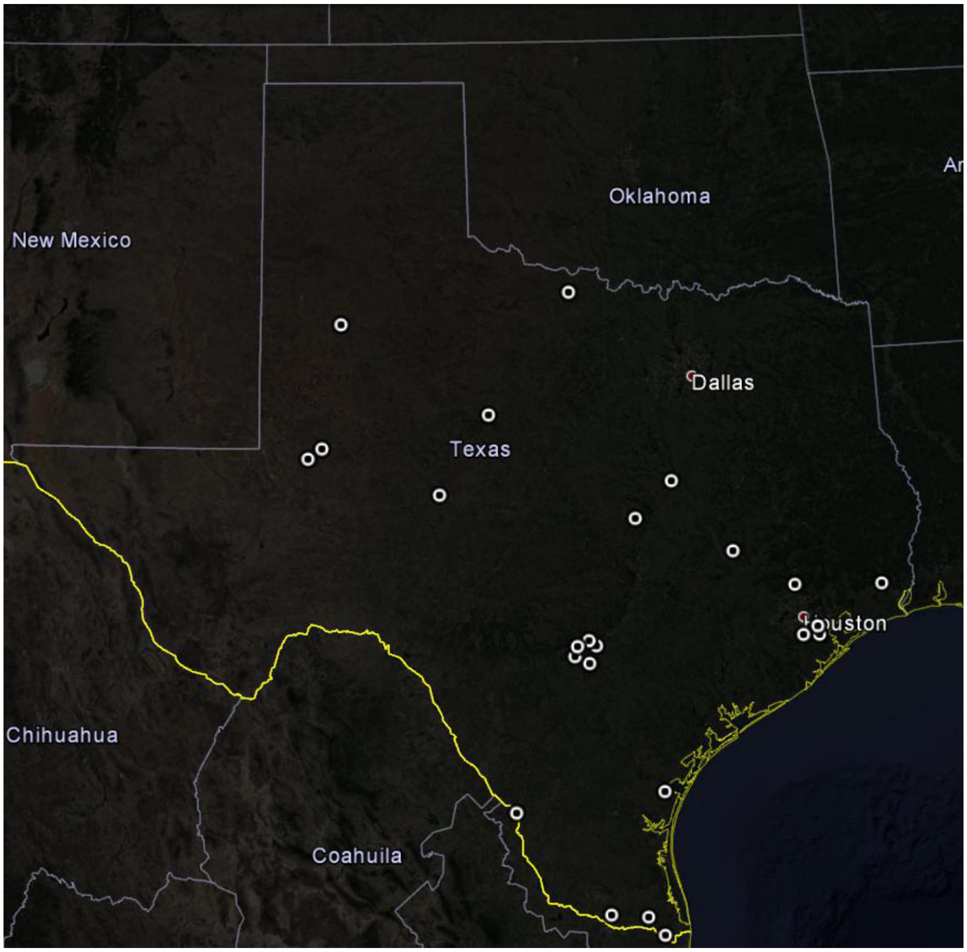
Notes: Franchise effect estimates are taken from a fixed effects regression which includes control variables used in Specification (4) in Table 2.4. A separate franchise effect is estimated for each store.

Figure 2.4: Locations of Company Owned Buffalo Wild Wings Stores



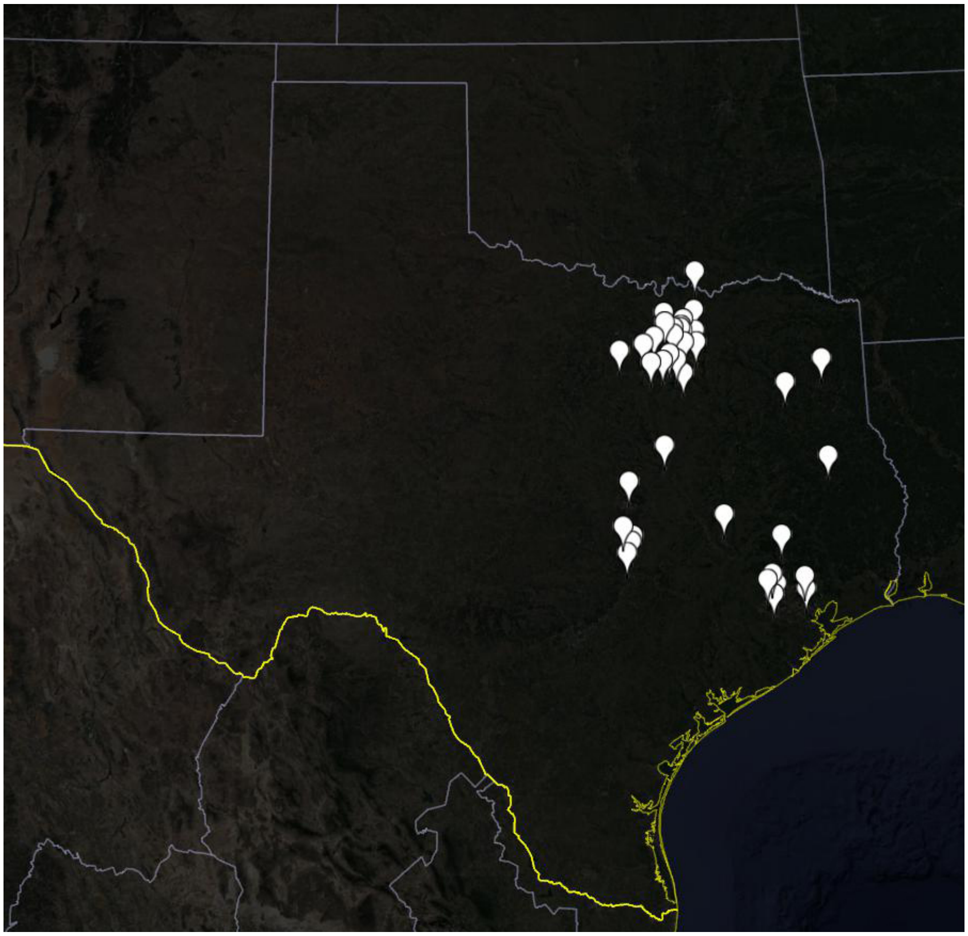
Notes: All stores open at any time between 2006 and 2013 are included.

FIGURE 2.5: Locations of Franchised Buffalo Wild Wings Stores



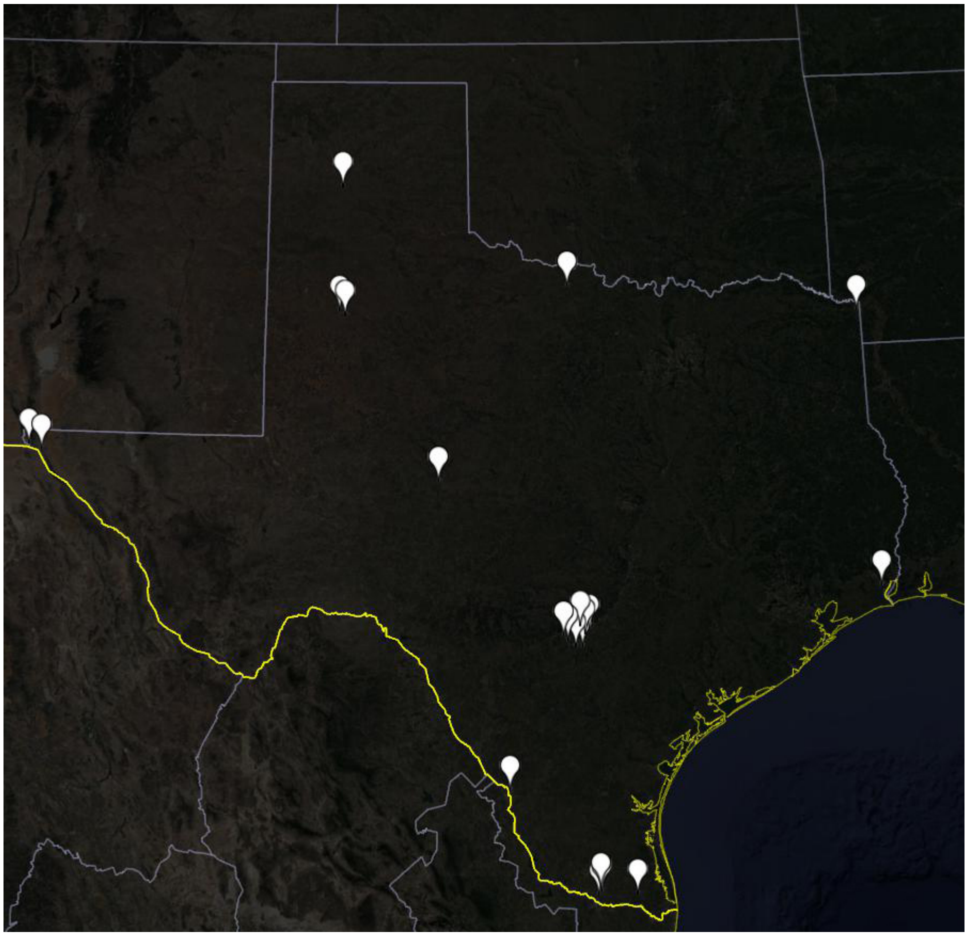
Notes: All stores open at any time between 2006 and 2013 are included.

Figure 2.6: Buffalo Wild Wings Located Near Company Owned Applebee's Stores



Notes: Graph shows all Buffalo Wild Wings located within five miles of an Applebee's store that was originally company-owned.

Figure 2.7: Buffalo Wild Wings Located Near Franchised Applebee's Stores



Notes: Graph shows all Buffalo Wild Wings located within five miles of an Applebee's store that opened prior to 2007 and was originally franchised.

CHAPTER 3

STRUCTURAL MODEL

During my sample period, there were significant changes in the nearby populations and competitive landscapes of Applebee's stores. It is important for me to be able to distinguish a positive franchise effect from differences in revenue caused by such changes. For this reason, I turn to a more structural model. Specifically, I create a utility-based model where individuals take restaurant characteristics and travel costs into consideration when choosing how to allocate their restaurant budgets. This model will also allow me to estimate how franchising affects consumer utility. The model generates revenue predictions for every restaurant in my data set. I use nonlinear least squares to select parameters that minimize the difference between observed revenues and predicted revenues. Results indicate that franchising a store has a positive impact on revenues. By simulating a counterfactual in which the stores are not franchised, I calculate the effects of franchising on firms and and competitors. I find that franchising a store increases its revenues by 7 percent, and that about 30 percent of this additional revenue comes from consumers switching away from competing national chains. I also find that consumer utility gains from visiting a franchised rather than company-owned store are equivalent to utility gains that would be experienced by a 2.8 mile reduction in travel distance to a company-owned store.

3.1 Utility Model

I now introduce a model of consumer preferences for restaurants. These preferences are used to predict purchase decisions and subsequent store revenues. The store revenues before and after an exogenous ownership change can be used to find the effect of franchising. I estimate this model in Section 3.2. Consumers are defined by two factors: their incomes and where they live. All consumers live in the population-weighted centroid of their zip codes and have an income equal to the median per-capita income for their zip codes. Thus, all consumers within a zip code are identical. Time is indexed by $t = 1, ..., T$. I model quarterly sales, so each t represents a quarter. Zip code i has a population of n_{it} at time t.

The model proceeds as follows. First, the consumer decides how much money to spend at restaurants during time t. A consumer in zip code i at time t has income I_{it} and budgets b_{it} for eating out. Consumers spend a fixed share of their income at restaurants:

$$b_{it} = Q_{it}\eta I_{it}. \tag{3.7}$$

I allow the share of income spent at restaurants to vary by income quartile and define $Q_{it} = [Q^1_{it},\ Q^2_{it},\ Q^3_{it},\ Q^4_{it}]$ as a vector of indicator variables; $Q^q_{i,t} = 1$ if zip code i is in income quartile q at time t. Similarly, I define $\eta = [\eta^1,\ \eta^2,\ \eta^3,\ \eta^4]$ as a vector of parameters. Thus the share of income spent at restaurants by an individual in income quartile q is equal to η^q.

Note that this method is different from models that assume each individual demands a certain quantity of a good. For example, Berry et al. (1995) consider consumers who purchase, at most, a single car. I consider a consumer who has a fixed budget for restaurants and is deciding how to spend this money. This sort of model is used by Holmes (2011) and Ellickson et al. (2016); in both papers, the authors observe revenues but not prices and quantities.

Next, the consumer determines where to spend each dollar of their restaurant budget by examining all stores and choosing the one that offers the greatest utility. As I will detail later, my econometric model is based on matching predicted sales to observed sales. To improve the tractability of the model, I use different utility specifications for chain stores (as defined in Section 1.2: Applebee's, Buffalo Wild Wings, Chili's, and T.G.I. Friday's) and non-chain stores.

Chain store utility

If store j is a chain store, the utility that individual i gets from spending dollar d at store j at time t is

$$U_{ijtd} = A_{jt}\alpha + F_{jt}\beta + \gamma H_{jt} + D_{ij}\tau + \epsilon_{ijtd}. \tag{3.8}$$

I define A_{jt} as a vector of indicator variables, $[A_{jt}^{APLC},\ A_{jt}^{APLF}, A_{jt}^{APLN}\ A_{jt}^{BWW},\ A_{jt}^{CHI},\ A_{jt}^{TGI}]$, that identify chain affiliation and, in the case of an Applebee's store, its original owner. $A_{jt}^{BWW} = 1$ if store j is a Buffalo Wild Wings and $A_{jt}^{BWW} = 0$ otherwise. A_{jt}^{CHI} (Chili's) and A_{jt}^{TGI} (T.G.I. Friday's) are defined similarly. I divide Applebee's stores into three groups, depending on their original ownership. $A_{jt}^{APLC} = 1$ if store j is an Applebee's that was company-owned when it first opened. $A_{jt}^{APLF} = 1$ if store j is an Applebee's that was franchised when it first opened *and* store j was opened prior to 2007. $A_{jt}^{APLN} = 1$ if store j is an Applebee's that opened in 2007 or later. Thus, $\alpha = [\alpha_{jt}^{APLC},\ \alpha_{jt}^{APLF},\ \alpha_{jt}^{APLN},\ \alpha_{jt}^{BWW},\ \alpha_{jt}^{CHI},\ \alpha_{jt}^{TGI}]$ is a vector of parameters representing the utility intercept for each store type.

In order to identify the effect of franchising on store performance, F_{jt} is defined as an indicator variable where $F_{jt} = 1$ if store j is an Applebee's store that was originally company-owned and t is a time period after 2007. Thus, for stores that change ownership, $F_{jt} = 1$ if the store is franchised at time t. Note that for Applebee's stores that are always franchised, F_{jt} equals zero for all values of t. This means that α^{APLF} and α^{APLN} account for any benefits due to franchisee ownership of these stores; because these stores never experience an ownership change, the effect of franchising cannot be specifically identified. The additional utility that a consumer receives from shopping at a franchised store, relative to the utility received if the same store were company-owned, is equal to β. In other words, if a store switches from company-owned to franchised, consumers will get additional utility in the amount of β for each dollar spent at that store.

As discussed earlier, existing literature suggests two main avenues by which franchising can provide additional utility to consumers and thereby increase demand. The first is moral hazard. Because a franchisee has higher-powered incentives than a manager, she may be more motivated than a manager to maximize store performance. For example, a franchisee may be willing to spend more time reviewing resumes and interviewing candidates in order to ensure that all employees are friendly and professional. Better employees will translate into a better customer experience. The second is local expertise. A franchisee may have a better sense of local tastes and therefore be better able to customize their store to fit the market. For example, an Applebee's franchisee may adjust restaurant decor or implement new menu items to appeal to the local market.[32]

It is also possible that IHOP implemented company-wide policies that affected the revenues of all Applebee's stores. To account for this, I define H_{jt} as an indicator variable equal to 1 if store j is an Applebee's and t is a time period after 2008.[33] Thus, γ is a parameter that represents the effect that IHOP's corporate ownership has on the revenue of all Applebee's stores.

To account for travel costs, D_{ij} equals the distance from an individual in zip code i to store j in miles. The disutility of travel is represented by τ, a parameter that I expect to be negative. Thus, a consumer will get less utility from a store located far from her home. As a result, stores located in highly populated areas will get more customers, all else equal. Finally, ϵ_{ijtd} is a random error term that follows the extreme value distribution for a nested logit; the nesting structure is described below.

[32]These examples are not purely hypothetical. As discussed in footnote 11, Applebee's allows for the possibility of a franchisee introducing new menu items. Applebee's stores are also often decorated with local sports memorabilia.

[33]I use 2008 rather than 2007 as a cutoff here to ensure that there is a sufficient amount of time for IHOP to have implemented new policies.

Non-chain store utility

Non-chain stores are aggregated by zip code. Specifically, I assume that all non-chain stores within a zip code are grouped together at the centroid of the zip code as one "outside option," and that the only revenue observed is the total revenue of all stores. This could be compared to a food court at a mall where sales at all of the restaurants in the food court are combined. There is an outside option for each zip code that contains a non-chain store.

Utility for outside option j is:

$$U_{ijtd} = Q_{it}\phi + \rho \log N_j + D_{ij}\tau + \epsilon_{ijtd}.$$

The income quartile indicator Q_{it} is included to allow for the utility of non-chain stores, relative to that of chain stores, to differ by income. Individuals' utility from the outside option is therefore given by the parameter $\phi = [\phi_1,\ \phi_2,\ \phi_3,\ \phi_4]$. If, relative to chain stores, consumers in the fourth income quartile like non-chain stores more than consumers in the first income quartile, then ϕ_4 will be greater than ϕ_1. N_j is the number of non-chain stores included in j (i.e. the number of non-chain stores in zip code j). The $\rho \log N_j$ term is included because I expect consumers to prefer zip codes with more stores. I have two reasons for this prediction. First, a zip code with more stores is more likely to have a store that is located near the consumer's house. Second, a zip code with more stores is more likely to have the type of food that the consumer is looking for. Thus, ρ is expected to be positive. I also expect that this benefit diminishes as the number of stores increases. This is because, once there are a large number of stores, it is less likely that an additional store will be more preferred, in terms of geography or food type, than the existing options. The log operator is used to account for these diminishing returns.

Nesting

To account for the possibility that consumers' tastes for Applebee's are correlated with their tastes for other chain restaurants, I use a nested logit model with two nests: one nest contains chain restaurants and the other nest contains outside options. $\lambda \in (0,1)$ is a measure of correlation. If $\lambda = 1$, there is no correlation among taste shocks and the model simplifies to a standard multinomial logit. If $\lambda = 0$, taste shocks within a nest are perfectly correlated.[34] I define J_t^C as the collection of all chain stores at time t and J_t^O as the collection of all outside options at time t.

Store revenues

I define $\bar{U}_{ijt}$ as follows: $\bar{U}_{ijt} = U_{ijtd} - \epsilon_{ijtd}$. For a given chain store, the only differences in $\bar{U}_{ijt}$ among consumers are due to different travel distances and, in the case of Applebee's, whether the store was originally franchised. The share of an individual's budget spent at a store is equal to the probability of the individual choosing to spend a given dollar at that store; probabilities follow the standard formulas for the nested logit model. If store j is a chain store, the total share of consumer i's budget spent at store j at time t is

$$p_{ijt} = \frac{e^{\bar{U}_{ijt}/\lambda}\left(\sum_{k \in J_t^C} e^{\bar{U}_{ijt}/\lambda}\right)^{\lambda-1}}{\left(\sum\limits_{k \in J_t^C} e^{\bar{U}_{ijt}/\lambda}\right)^{\lambda} + \left(\sum\limits_{k \in J_t^O} e^{\bar{U}_{ijt}/\lambda}\right)^{\lambda}}. \tag{3.9}$$

If j represents one of the outside options, the total share of consumer i's budget spent at outside option j at time t is

$$p_{ijt} = \frac{e^{\bar{U}_{ijt}/\lambda}\left(\sum_{k \in J_t^O} e^{\bar{U}_{ijt}/\lambda}\right)^{\lambda-1}}{\left(\sum\limits_{k \in J_t^C} e^{\bar{U}_{ijt}/\lambda}\right)^{\lambda} + \left(\sum\limits_{k \in J_t^O} e^{\bar{U}_{ijt}/\lambda}\right)^{\lambda}}.$$

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[34] A more thorough discussion of the nested logit can be found in Davidson and MacKinnon (2004).

While each consumer has each store in their choice set, the disutility of travel should lead to stores far from an individual's home being chosen with a low probability.[35]

Individual purchase shares can be aggregated to find store revenues. Consumer i spends a total of

$$R_{ijt} = p_{ijt} b_{it} \tag{3.10}$$

at store j at time t. Total revenue for store j is

$$R_{jt} = \sum_{i \in Z_t} n_{it} R_{ijt}, \tag{3.11}$$

where Z_t represents the set of all zip codes at time t.

I do not observe prices and quantities and therefore do not attempt to estimate demand. However, as discussed in Jin and Leslie (2003), an increase in revenues can be attributed to an upward shift of the demand curve.[36] In my model, for a given location at a given time, any changes in store revenues are due to changes in $\bar{U}_{ijt}$. Thus, controlling for changes in population and budgets, if a store earns more revenue, it must be because the utility it provides consumers increased. If store j changes from being company-owned to franchised, F_{jt} will change from 0 to 1 and, if β is positive, $\bar{U}_{ijt}$ will increase for all consumers. The magnitude of β will determine the size of the increase in $\bar{U}_{ijt}$ and the subsequent increase in R_{jt}. Therefore, estimating the effect of franchising on revenues is analogous to estimating β.

[35] I also estimated specifications in which choice sets were limited to locations within 75 miles of the consumer. Results are similar to those presented in this paper.

[36] This is true even if I allow for the possibility that a franchisee can reduce marginal costs. If the cost reduction is accompanied by a price reduction, then an increase in revenues may be due to a decrease in prices. However, because my model is concerned with utility *per dollar spent*, a reduction in price has the same effect on $\bar{U}_{ijt}$ as an increase in quality.

3.2 Econometric Analysis

I now explain how I adapt the model from Section 3.1 for estimation, using the sale of Applebee's to IHOP and subsequent franchising of all company-owned Applebee's stores to identify the effect of franchising on store-level alcohol revenues.

There are 671,426 revenue observations in my data set, where an observation is the alcohol revenue of a single store in a single quarter. However, as discussed earlier, I aggregate non-chain stores into aggregate stores. This reduces the number of observations to 81,138. My econometric model is based on using nonlinear least squares to minimize the difference between predicted revenue and observed revenue for these observations.

I now finalize a list of parameters to estimate and detail my estimation method. As described in Section 3.1, I aggregate individual expenditures to find store revenues. I define $\theta = (\alpha,\ \beta, \gamma,\ \tau,\ \phi,\ \rho,\ \lambda)$ as the set of parameters that determine how individuals allocate their budget across stores. Because I do not observe when in 2008 the ownership changes occur, I separate F and β into two components, one for 2008 and one for all subsequent years: β^{08} is an estimate of the franchise effect in 2008 and β^{09} is an estimate of the franchise effect in 2009 and later. I consider β^{09} to be a more accurate estimate of the franchise effect, because all stores are definitely franchised starting in 2009. F_{jt}^{08} and F_{jt}^{09} are defined similarly. The share of income spent on on-premises alcohol consumption is represented by the vector η, which is a parameter to be estimated. $\Theta = (\theta,\ \eta)$ is the full set of parameters. In logit demand models, utilities are relative, so a normalization is needed. I set $\phi_1 = 0$, meaning that a consumer in the lowest income quartile eating at an outside option that contains a single store without having to travel receives a utility of zero. Expressions for budgets, utilities and expenditure shares can now be expressed as functions of parameters, i.e. $b_{it}(\theta)$, $\bar{U}_{ijt}(\theta)$, and $p_{ijt}(\theta)$.

Consumers in zip code i spend a total of

$$R_{ijt}(\Theta) = p_{ijt}(\theta) b_{it}(\eta) n_{it}$$

at store j at time t. Total predicted revenue for store j at time t is

$$R_{jt}(\Theta) = \sum_{i \in Z_t} R_{ijt}(\Theta).$$

I attribute all differences between predicted revenue, $R_{jt}(\Theta)$, and observed revenue, R^O_{jt}, to measurement error. I model this measurement error as a mean-zero random multiplicative shock, u_{jt}, that affects each store and is independent across stores and time periods:

$$R^O_{jt} = e^{u_{jt}} R_{jt}(\Theta).$$

Nonlinear least squares estimation produces the estimator

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \sum_{t=1}^{T} \sum_{j \in J_t} \Big(\log(R^O_{jt}) - \log\left(R_{jt}(\Theta)\right) \Big)^2,$$

where J_t is the union of J^C_t and J^A_t. This estimator is consistent and asymptotically normal. Standard errors are computed by the appropriate transformation of the Hessian matrix.[37]

3.3 Results

Results for this model are presented as Specification (1) in Table 3.1. I next add a linear time trend to the model in an attempt to separate gradual changes in store revenues from abrupt changes caused by the IHOP sale. This accounts for the possibility that, overall, Applebee's was becoming more or less popular over time. For example, it may be that its brand reputation was improving or that American diners were developing a taste for Applebee's fare. These results are shown as Specification (2) in Table 3.1. There is a positive and statistically significant upward trend. Because this trend is statistically significant and significantly improves the fit of my model, I consider its results to be the most reliable and discuss them in this section.

[37]See Wooldridge (2010) for a full explanation of the nonlinear least squares estimator.

The most important result is that the franchise effect (β^{09}) is positive and statistically significant, with a coefficient of 0.051 and $p < 0.01$. This means that consumers get additional utility equal to 0.051 when visiting a franchised Applebee's compared with a company-owned Applebee's. The coefficient itself does not provide an intuitive description of the value of franchising. However, it can be compared with other estimated coefficients to draw meaningful interpretations of the additional utility consumers receive from a franchised store. I next use the estimated values of travel cost (τ) and value of each outside-option store (ρ) to perform such comparisons.

As expected, travel cost is negative, with a coefficient of -0.018 and $p < 0.01$. By dividing β^{09} by τ, I find that a consumer would be indifferent between a franchised Applebee's and an otherwise identical company-owned Applebee's that is located 2.8 miles closer to her home. The estimate of ρ is positive, indicating that consumers prefer outside options that contain more restaurants. The coefficient is equal to 0.893 with $p < 0.01$. The increase in utility from shopping at an Applebee's store that becomes franchised is equivalent to the utility increase that occurs when the number of stores in an outside option increases from 14 (the average number of stores in an outside option) to 14.8. Utility calculations for all specifications are shown in Table 3.2.

I find that the sale to IHOP had a positive impact on revenues for Applebee's stores of all ownership structures. As mentioned in Section 2.1, this may be due to new chain-wide policies such as new menu items. The additional utility enjoyed by patrons of an Applebee's store due to IHOP's ownership is equivalent to the utility gain from an 3.1 mile decrease in travel distance to that store.

The 2008 effect of franchising is negative but not significant. There are two likely explanations for this result. The first is that, as discussed earlier, it is possible that stores that changed ownership were company-owned during some part of 2008 and therefore any franchise effect would be diminished. The second is that, because there are relatively few observations where $F_{jt}^{08} = 1$, it is difficult to separate causality from random noise.

Budget coefficients are displayed as dollars spent each a quarter per \$10,000 in annual income. Individuals in the second income quartile spend the greatest percentage of their income and individuals in the highest income quartile the least. Preference for chain restaurants relative to other stores decreases as income quartile increases. The nesting coefficient is 0.68 with $p < 0.01$, indicating that preferences for Applebee's stores are correlated with those for other chain stores.

I turn next to α, the vector of utility intercepts. Each component of α can be thought of as an approximation of each store type's unobserved utility determinants. For example, Buffalo Wild Wings stores tend to have higher alcohol revenues than other chains. One possible explanation for this is that Buffalo Wild Wings stores are located in areas with higher populations or less competition. An alternative explanation is that, all else being equal, Buffalo Wild Wings stores generate more revenues than other chain stores due to factors that are unobservable to the researcher. For example, it may be that, because Buffalo Wild Wings markets itself as a sports bar, it tends to draw customers who will stay longer and buy more alcohol. These unobservable factors determine α^{BWW}. I find that α^{BWW} is greater than the other components of α, indicating that there are unobserved factors leading to Buffalo Wild Wings stores having greater revenues.

I am most interested in α^{APLC}, α^{APLF}, and α^{APLN}. While α^{APLF} and α^{APLN} also reflect any increase in utility due to franchisee ownership, α^{APLC} does not. The post-2008 utility intercept for an Applebee's store that changes ownership is given by $\alpha^{APLC} + \beta^{09}$. This reflects both the original intercept as well as the additional utility provided by franchising. I next compare α^{APLF}, α^{APLN}, and $\alpha^{APLC} + \beta^{09}$; these intercepts all include the benefits from franchising, so remaining differences indicate differences in utility due to unobserved location quality. I find that $\alpha^{APLC} + \beta^{09} > \alpha^{APLF}$, meaning that stores that were initially company-owned tended to be located in better locations than those that were initially franchised, because Applebee's chose to own the stores with the best unobservables, which supports my earlier hypothesis and corroborates the findings from the reduced form regressions. I also find that α^{APLN} is between $\alpha^{APLC} + \beta^{09}$ and α^{APLF}. This is likely because, after the sale to IHOP, there was no longer any ownership selection, so α^{APLN} includes both the good and bad locations.

While this method estimates the effect of franchising on stores that change ownership, this may be a lower bound on the average effect of franchising on all Applebee's stores (not just those that were initially company-owned). In addition to choosing to own the best locations, Applebee's may have also chosen to own the locations where franchising would have provided the smallest benefit. For example, suppose that there is a possible location that is next door to Applebee's corporate headquarters. Applebee's may believe that, because the store is so close, they will avoid the monitoring difficulties and local inexpertise that typically plague company-owned stores.[38] If this is the case, they may find that the benefits of franchising are negligible and instead decide to own the store. On the other hand, the stores that would see the biggest benefit from franchising are most likely to be initially franchised; these stores do not experience an ownership change and are not used to estimate the franchise effect. One way to investigate this further would be to find an instance where an exogenous event caused franchised stores to become company-owned.

Additional time trends

Next, I combine the time trend described above with a linear time trend that applies only to Applebee's stores that were initially company-owned. This accounts for the possibility that the stores that were initially company-owned were improving throughout my sample, and that this improvement was greater than the overall improvement occurring in Applebee's stores. When I include this trend, the estimated effect of franchising becomes much smaller and statistically insignificant. However, the trend itself is not statistically significant, and the addition of the trend adds very little to the predictive power of the

[38]Kalnins and Lafontaine (2013) provide evidence that increasing the distance from a store to its corporate headquarters decreases store performance.

model. (The sum of squared residuals decreases by 0.0006 percent)

One possibility for the positive trend of company-owned stores is that these stores were located in areas where preferences for Applebee's were increasing over time. For example, there were five stores in Austin at the time of the sale to IHOP, all of them company-owned. There may have been an unobserved demographic change occurring in Austin during my sample period, where people who like Applebee's were moving into the city and those who dislike Applebee's were moving out. To account for this possibility, I combine the linear time trend for all Applebee's used in Specification (2) with an additional time trend. This time trend applies to both Applebee's stores that were company-owned and other chain stores that are located within 15 miles of those Applebee's stores. I assume that, if tastes for Applebee's are increasing, tastes for other chain stores are increasing as well. (Continuing the earlier example, if the new residents of Austin have a taste for Applebee's, it seems likely that they would have similar feelings for Chili's.) I also include an additional intercept term to distinguish any trend from the possibility that these stores were in locations with better unobservables. Results are shown as Specification (4) in Table 3.1. This new intercept is positive, with a coefficient of 0.126 and $p<0.01$. The new trend is negative with $p<0.01$ but very small in magnitude, with a coefficient of -0.0027. Overall, because the intercept is much larger than the trend, the overall effect is positive for all time periods in my sample. This indicates that company-owned Applebee's were located in areas where preferences for chain restaurants were especially high. The franchise effect is positive, with a coefficient of 0.09 and $p < 0.01$.

Adaptation

I next adjust the model to allow for non-Applebee's chain stores that were located near an Applebee's store that changed ownership to adapt to the Applebee's ownership change. For example, it may be that a nearby Chili's store was able to copy customizations made by the new Applebee's franchisee or that it faced competitive pressure to improve its offerings. I also include an additional intercept term for these stores. This intercept term is added to the store's value of α and distinguishes an adaptation following the IHOP sale from the possibility that these stores were in locations with better unobservables. I find that the coefficient on this intercept term is positive but not statistically significant. Perhaps surprisingly, the adaptation coefficient is actually negative, indicating that chain stores responded to the Applebee's franchising by getting worse. One possible explanation for this is that the new Applebee's franchisees hired away the best employees of these competing stores. Alternatively, it may be that the new franchisees were especially effective at targeting customers of the other chain stores, perhaps by copying the menu items or marketing strategies of these stores. If the additional revenue earned by Applebee's stores that changed franchise status came disproportionately from consumers switching away other chain stores, this could result in a negative adaptation coefficient. Complete results are shown as Specification (5) in Table 3.1.

3.4 Simulations

To estimate the magnitude of the franchise effect, I simulate a scenario in which the franchise effect (β^{09}) equals zero. This allows me to compare predicted revenue to what store revenues would have been if there were no positive impact from franchising or if the stores had not changed ownership. In this section, I discuss results from Specification (2). Results for other specifications are shown in Table 3.2.[39]

I find that franchising increases average store revenue by 7.4 percent. In 2013, average

[39] For Specification 5, because the nearby chain stores get worse following the ownership change, they lose revenues to both Applebee's stores and aggregate stores. As a result, their net revenue loss is greater than the increase in revenue experienced by the Applebee's stores that become franchised. Similarly, while aggregate stores lose some revenue to the Applebee's stores that change ownership, they gain a substantial amount of revenue at the expense of the non-chain stores that get worse. Overall, aggregate stores see their revenue increase following the Applebee's ownership change. This explains the unusual values for the "Share" rows for this specification in Table 3.2. This odd result, where an Applebee's ownership change results in a net revenue gain for aggregate stores, is a consequence of the nested logit; any time an alternative gets worse, it loses consumers to every other store. Because aggregate stores earn much more revenue than Applebee's stores, it is unsurprising that a majority of the revenue lost by chain stores goes to aggregate stores. An alternative model could allow the nesting parameter to change; this would be a better way to model the theory that the new franchisees are especially effective at targeting chain restaurant customers.

annual alcohol revenues were \$479,000 per Applebee's store, meaning that franchising brought in an additional \$35,000 in alcohol sales per store. Because there is no outside or composite good in this model and budget formation is independent of restaurant options, all additional revenue due to franchising comes from individuals switching away from other restaurants. Specifically, 30.3 percent percent of this additional revenue comes from individuals switching away from non-Applebee's chain stores, and 68.4 percent of the revenue comes from individuals switching away from non-chain stores. An additional 1.3 percent comes from individuals switching away from another Applebee's store. I also examine the variation in the franchise effect between stores. While each store receives the same increase to its utility intercept, differences in competitive landscapes will result in stores having heterogeneous responses to the increase. I find that there is relatively little variance in the magnitude of the franchise effect among stores; for the first quarter of 2013, the median store revenue increase due to franchising was 7.3 percent, and half of all stores saw an increase between 7.29 percent and 7.38 percent.

To estimate the impact of the IHOP sale, I simulate a counterfactual in which the effect of IHOP's ownership on store revenues, γ, is equal to zero. Note that, in this counterfactual, I do not set β^{09} to zero; I am isolating the impact that IHOP's ownership had on all stores from the benefits from franchising experienced by stores that change ownership. I find that IHOP's ownership increased statewide Applebee's revenues by 7.8 percent. I call this the "IHOP effect" in Table 3.2. Adding this IHOP effect to the estimated franchising effect of 7.4 percent, I find that the total revenue increase experienced by Applebee's stores that changed ownership is approximately 15 percent.

Store Differences

In the above model, predicted Applebee's store revenues are determined by three factors: observables, unobservables, and ownership. Observables are all determinants of store revenue which are observed by the econometrician; in this case, that includes the location and type (chain or non-chain) of all competing stores and the locations and incomes of all consumers. Unobservables include everything that affects the potential revenue of a location and is not observed by the econometrician. For example, if a store's parking lot is hard to access because it requires making a left turn at a busy intersection, that could negatively affect store revenues. Finally, as found above, a store's ownership significantly affects its performance. In this section I decompose the revenue for each Applebee's store into these three components. This allows me to determine, for example, whether stores that were initially company-owned have better unobservables than those that were initially franchised.[40]

To gain a better understanding of how both observable and unobservable determinants of location quality affect store performance, I conduct three counterfactuals, using Specification (2) of Table 3.1 as my baseline. I first simulate a situation in which Applebee's stores differ only in observables and no store benefits from franchising. Next, I allow stores to have differences in unobservables but continue to not allow any store to benefit from franchising. Finally, I simulate the full estimated model, which allows for both unobservable differences and benefits from franchising. In order to conduct these three counterfactuals, I make one modification to the model. As discussed in Section 3.3, differences between α^{APLF}, α^{APLN}, and $\alpha^{APLC} + \beta^{09}$ reflect differences in utility due to unobserved location quality. I subtract $\beta^{09}$from each of these values when defining utility intercepts so that the intercept reflects a scenario in which stores receive no benefit from franchising.[41]

For the first counterfactual, in order to isolate the effect of observables, I give each Applebee's store a utility intercept of α^{APLN} and set β^{08} and β^{09} equal to zero. Thus, all differences in simulated revenues are due to differences in store location. For the second counterfactual, I assign each Applebee's type its estimated utility intercept (α^{APLC},

[40]This comparison is analogous to the logit regressions described in Section 2.1 that used post-franchising revenue as an explanatory variable.

[41]This requires the assumption that all stores receive the same benefit, equal to β^{09}, from franchising.

α^{APLF}, or α^{APLN}) but, as before, set β^{08} and β^{09} equal to zero. This allows for stores with different ownership histories to have differences in unobservable location quality. For the final counterfactual, I make no adjustments to the estimated parameters. Median and average store revenues for the three counterfactuals for all stores open prior to the IHOP sale are shown as Specifications (1), (2), and (3) in Table 3.3.

Comparing the median revenues of the different store types for the three counterfactuals provides some interesting results. Looking at the first specification, the initially franchised stores have a median simulated revenue that is 38% greater than the stores that were initially company-owned. This means that the initially franchised stores are in locations that have better observables; in the context of this model, it means they are in locations with more people and fewer competitors. Turning now to Specification (2), I find that allowing each store to have its originally estimated utility intercept (α^{APLF} or α^{APLC}) has substantially different effects on the two store types. Relative to the results of Specification (1), the median store revenue increases for initially company-owned stores and decreases for initially franchised stores. This is expected, as α^{APLN}, the utility intercept assigned to both ownership types in Specification (1), is greater than α^{APLF} and less than α^{APLC}. Thus, by assigning each store its estimated utility intercept, originally franchised stores see their intercept decrease while originally company-owned stores see their intercept increase. As a result of this, in absence of any franchise effect, the simulated median store revenue for initially company-owned Applebee's stores, is slightly greater than the simulated median store revenue of initially franchised Applebee's stores. Finally, in Specification (3), stores are impacted by the franchise effect. As with the previous specification, stores that were initially company-owned have higher predicted sales than those that were initially franchised. From Specification (2) to Specification (3), both store types saw an increase in revenues of about seven percent; unsurprisingly, this is approximately the same franchise effect found in Specification (2) of Table 3.1, the results of which are the coefficients used in this simulation analysis.

To summarize, on average, the two store types have similar revenues. However, stores that were initially franchised tend to be in locations that are observably better (e.g. higher population and less competition, especially from competing chain restaurants), while stores that were initially company-owned tend to be in locations that are unobservably better (e.g. located near people who are especially fond of chain restaurants). Regarding the second observation, there are at least two possible reasons for this. The first is discussed in Section 1.3: the franchisor chooses to own the best locations, including those that are better in ways that are unobservable to the researcher. A second is that it may be the case that, within a given market, the franchisor is better able to find a high revenue location. This is, however, different from what would be predicted by a theory of local expertise, since it seems likely that a local franchisee would be better able to assess the profit potential of each possible location. One possibility is that the franchisor has the resources necessary to commission a market research study or use data analytics to assess location quality, while a franchisee will tend to rely on experience and intuition. This is an area for further research.

3.5 Conclusion

In this paper, I used the sale of Applebee's to IHOP and subsequent franchising of all Applebee's stores in the state of Texas to estimate the effect of franchising on store revenues. I find that franchising increased store alcohol revenues by approximately seven percent. This supports the hypotheses of many theoretical and empirical papers which predict that, all else equal, franchised stores will outperform company-owned stores. These results only account for increases in alcohol revenue. I am unable to determine what effect franchising has on food revenues, or if some of this increase is caused by Applebee's customers switching from food consumption to alcohol consumption. I also am unable to model how profits are affected.

The estimated franchise effect of seven percent is substantially different from the franchise effect estimated in the reduced form models in Chapter 2, which ranged from 15 percent to 19 percent depending on the demographic variables used. One possible cause for this difference is the different ways that the models account for competing chain stores. In the structural model, chain stores are separated out from other stores and tracked individually. The nesting coefficient shows the importance of doing this, as preferences for different chain restaurants are positively correlated. This means that revenues for a given Applebee's store are significantly affected by the entrance or exit of a nearby chain store. The reduced form model does not differentiate between chain stores and non-chain stores; the only way that the influence of competing stores is modeled is through the Competition variable, which is simply a measure of total restaurant employment. In future research, I plan to add a variable that accounts for the influence of competing chain restaurants by identifying the number of competing chain restaurants located in the same county as a given Applebee's store.

The economics of franchising have recently been pushed into policy discussion. In December 2014, the National Labor Relations Board issued a ruling that McDonald's and its franchisees are "joint employers" of McDonald's employees who work at franchisee-owned stores.[42] Franchise trade groups generally opposed the decision, arguing that the new laws would reduce the autonomy of franchisees and lead to fewer franchised businesses. My research suggests that policies that lead to fewer franchised stores will have a negative impact on store revenues and consumer utility.

[42]The National Labor Relations Board describes itself as "an independent federal agency that protects the rights of private sector employees to join together, with or without a union, to improve their wages and working conditions."

TABLE 3.1: Parameter Estimates

Param.	Description	(1)	(2)	(3)	(4)	(5)
β^{09}	Franchise effect	0.065***	0.051**	0.011	0.09***	0.038
		(0.026)	(0.028)	(0.064)	(0.032)	(0.044)
γ	IHOP sale	0.187***	0.055**	0.076**	0.033	0.058
		(0.022)	(0.030)	(0.040)	(0.038)	(0.052)
β^{08}	2008 effect	0.040*	-0.024	-0.033*	-0.018	-0.022
		(0.032)	(0.025)	(0.025)	(0.038)	(0.051)
τ	Travel cost	-0.018***	-0.018***	-0.018***	-0.019***	-0.019***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.005)
ρ	Per-store utility	0.898***	0.893***	0.894***	0.916***	0.905***
		(0.034)	(0.030)	(0.023)	(0.041)	(0.034)
λ	Nesting parameter	0.682***	0.678***	0.679***	0.695***	0.687***
		(0.026)	(0.023)	(0.018)	(0.031)	(0.016)
η_1	Budget 1	10.182***	10.181***	10.181***	10.188***	10.186***
		(0.105)	(0.113)	(0.109)	(0.121)	(0.129)
η_2	Budget 2	14.467***	14.470***	14.470***	14.454***	14.459***
		(0.161)	(0.158)	(0.156)	(0.163)	(0.237)
η_3	Budget 3	8.251***	8.252***	8.252***	8.257***	8.256***
		(0.124)	(0.129)	(0.128)	(0.111)	(0.217)
η_4	Budget 4	7.274***	7.275***	7.274***	7.274***	7.274***
		(0.088)	(0.089)	(0.091)	(0.095)	(0.124)
ϕ_2	Outside 2	0.666***	0.664***	0.664***	0.644***	0.649***
		(0.032)	(0.032)	(0.034)	(0.036)	(0.047)
ϕ_3	Outside 3	0.733***	0.736***	0.736***	0.782***	0.785***
		(0.040)	(0.039)	(0.038)	(0.044)	(0.084)
ϕ_4	Outside 4	1.038***	1.041***	1.041***	1.057***	1.064***
		(0.036)	(0.037)	(0.037)	(0.04)	(0.045)
α^{APLC}	APLC intercept	0.463***	0.274***	0.253***	0.407***	0.342**
		(0.104)	(0.092)	(0.077)	(0.130)	(0.168)

Continued ...

Table 3.1: (continued)

Param.	Description	(1)	(2)	(3)	(4)	(5)
α^{APLF}	APLF intercept	0.281***	0.080	0.111*	0.113	0.121*
		(0.096)	(0.089)	(0.077)	(0.115)	(0.090)
α^{APLN}	APLN intercept	0.346***	0.125*	0.160**	0.166*	0.179***
		(0.107)	(0.096)	(0.089)	(0.123)	(0.063)
α^{BWW}	BWW intercept	1.071***	1.054***	1.056***	1.132***	1.093***
		(0.124)	(0.109)	(0.082)	(0.151)	(0.146)
α^{CHI}	CHI intercept	0.584***	0.568***	0.570***	0.633***	0.601***
		(0.106)	(0.093)	(0.071)	(0.129)	(0.062)
α^{TGI}	TGI intercept	0.640***	0.624***	0.626***	0.692***	0.658 ***
		(0.108)	(0.096)	(0.072)	(0.132)	(0.137)
	APL trend		0.007***	0.006***	0.008***	0.007**
			(0.001)	(0.002)	(0.001)	(0.004)
	COS trend			0.002		
				(0.003)		
	COS and market trend				-0.0027***	
					(0.0007)	
	COS market trend intercept				0.126***	
					(0.032)	
	Nearby adapt					-0.064**
						(0.032)
	Nearby adapt intercept					-0.053
						(0.058)
	SSR	32,136.83	32,128.69	32,128.51	32,120.43	32,119.00

Notes: Travel cost is expressed as the utility cost per mile travelled. Budget reflects dollars spent per $10,000 in annual income. "Outside" represents utility from aggregate stores. Budget and outside utility vary by income quartile. BWW, CHI, and TGI represent Buffalo Wild Wings, Chili's, and T.G.I. Fridays, respectively. APLC represents an Applebee's that was company-owned when it first opened. APLF respresents an Applebee's that was initially franchised and was opened prior to the IHOP sale. APLN represents an Applebee's that was opened after the sale to IHOP. Trends are linear time trends. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.2: Impact of Franchising - Utility Comparisons and Simulation Results

Empirical Specification	(1)	(2)	(3)	(4)	(5)
Equivalent distance reduction	3.6	2.8	0.6	2.1	2.0
Equivalent outside store increase	1.1	0.8	0.2	1.3	0.6
Franchise effect	9.4%	7.4%	1.5%	13.0%	6.6%
Share from outside.	68.7%	68.4%	68.6%	70.0%	-167.1%
Share from chain	30.0%	30.3%	30.2%	28.9%	269.9%
Share from APL	1.3%	1.3%	1.3%	1.2%	2.8%
IHOP effect	29.3%	7.8%	11.0%	4.6%	8.2%

Notes: "Equivalent distance reduction" reflects the reduction in distance to a company-owned Applebee's store that would produce a utility gain equal to the utility gain caused by franchising that store. "Equivalent outside store increase" reflects the increase in the number of stores in an outside option with the mean number of stores (14) that would produce a utility gain equal to the utility gain caused by a company-owned Applebee's store being franchised. "Franchise effect" indicates the percentage increase in revenue due to franchising. "Shares" are equal to the loss in revenue for that store type divided by the gain in revenue for Applebee's stores that become franchised; "chain", "outside", and "APL" indicate non-Applebee's chain stores, outside options, and Applebee's stores, respectively.

Table 3.3: Simulation Summary Statistics for Q1 2013

	(1)	(2)	(3)
Variation Among Stores			
Differences in Observables	Yes	Yes	Yes
Differences in Unobservables	No	Yes	Yes
Effect of Franchising	No	No	Yes
Originally Franchised Stores			
Average	119,681	104,592	112,096
Median	131,619	115,431	123,906
Originally Company Owned Stores			
Average	93,967	115,703	124,146
Median	95,313	117,720	126,261

Notes: Summary statistics are presented for simulated revenues for three different scenarios. In Specification (1), there are no unobservable differences in location quality and there is no franchise effect. In Specification (2), there are both observable and unobservable differences in location quality, but there is no franchise effect. Specification (3) is a simulation of the full estimated model; it includes both observable and unobservable differences in location quality and a franchise effect.

APPENDIX A

ESTIMATION OF UNOBSERVABLES IN SELECTION MODEL

Here, I explain how I use post-2009 revenues to find the effect of unobservable determinants of revenue on ownership selection. I write the logit model as

$$P_j = f(X_j\alpha + \gamma R_j), \tag{A.12}$$

where P_j is the probability that store j is franchised, X_j is a vector of observable variables and R_j is store j's average quarterly revenue for all periods after 2009; α and γ are parameters to be estimated. I define $f(t)$ as the standard binomial logistic function: $f(t) = 1/(1+e^{-t})$. Revenue is determined as follows:

$$R_j = X_j\beta + \xi.$$

By combining equations, (A.12) can be rewritten as

$$P_j = f(\tilde{\alpha}X_j + \gamma\xi),$$

where $\tilde{\alpha} = \alpha + \gamma\beta$. This shows that the estimated value of γ actually measures the impact of unobservable determinants of utility on the franchising decision.

APPENDIX B

DATA APPENDIX

Geocoding

According to the U.S. Census Bureau (USCB), zip codes are "not areal features but a collection of mail delivery routes." Because of this, the USCB created Zip Code Tabulation Areas (ZCTAs), which are "generalized areal representations" of zip codes. I use ZCTAs when geocoding zip code-level populations. I used multiple resources to geocode ZCTAs. First, I used MABLE, an online database maintained by the Missouri State Library. This database provides population-weighted centroids for every ZCTA in the United States, with 2010 census data being used for population weighting. For data prior to 2009, approximately 25 percent of zip codes (representing a share of population of approximately 2 percent) did not find a match in MABLE. For these, I used a privately maintained database at Boutell.com for matching. This database typically gives an area-weighted centroid. A small number of zip codes (representing about 0.01 percent of the population) were invalid. These were excluded from my analysis.

As mentioned earlier, per-capita income data is only available at the county level. To find the county that each zip code is located in, I use MABLE. Several zip codes include parts of multiple counties; MABLE lists the percentage of the zip code's population that resides in each county, as of the 2010 census. For these zip codes, I use whichever county contains the largest percentage of that zip code's population. For some zip codes, representing about 1% of all person-quarter observations in my sample, I was unable to assign a county to the zip code. For these locations, I assumed that the per-capita income was equal to the per-capita income for the state of Texas that quarter. Per-capita income data is calculated by the U.S. Bureau of Economic Analysis.

The Mixed Beverage Tax Receipts data contains addresses of each store, but not latitude and longitude coordinates. I used multiple resources to convert addresses to coordinates. I first used ArcGIS software. For about 10% of restaurants, ArcGIS was unable to determine the location of the establishment (this is most likely because the address in the Texas alcohol sales file was incorrect). For these locations, I used the web service SmartyStreets, which gets its geocoding data from the U.S. Postal Service. One advantage of this website is that, for stores which it cannot find an exact match, it generates coordinates that match the address as closely as possible. For example, if the name of a street can be found in the SmartyStreets database but the street number is invalid, then the coordinates generated will correspond to a location on the street. If the street name is not valid, the coordinates generated will correspond to the centroid of the location's zip code. In order to increase the number of stores that could be matched, I made some modifications to the address names. For example, I eliminate all suite numbers from store addresses, because including a suite number often prevented geocoding software from finding the street name. As mentioned in the paper, I was able to identify the exact locations of all stores identified as "chain stores" in the structural model.

In the structural model, non-chain stores are grouped at the zip code level. Because stores included in a given zip code typically have different coordinates, it is necessary for me to use an average store location in order to assign a single coordinate pair to each zip code. Specifically, for each quarter, I compute the average latitude and longitudes of the stores within each zip code and then average those averages across quarters. The averaging across quarters is necessary because my estimation routine requires that zip code locations remain constant over time.

All distances were calculated using latitude and longitude coordinates and an ellipsoidal model of the earth.

Sample selection

I model quarterly alcohol sales. Mixed beverage tax data is available on a monthly basis, so monthly sales are aggregated for each quarter. For the purposes of aggregation, stores are considered to be the same only if they have identical names and addresses. I believe this is a reasonable assumption because it appears that restaurants do not need to re-enter their names addresses when filing their tax forms each month; store names, even those with obvious typographical errors, typically do not change over time.

I excluded all observations that were the first or last quarter that a chain store was in the data set, because they likely represent sales for only a part of the quarter. If any store has less than $100 in sales during a quarter, that store's quarter is omitted from the data. The only restaurants specifically excluded were those in Dallas / Ft. Worth International Airport. These stores often reported their taxes as a single, combined entity, meaning that store-level sales could not be identified. One of these excluded stores was a T.G.I. Friday's.

Occasionally, the same store has multiple tax filings for the same month. When this occurs, I add the tax revenues and use the sum to calculate the store's total alcohol sales for that month.

Population and income data are available on a yearly basis. I smooth annual changes uniformly over the course of the year. Because annual per-capita income statistics are not available at the zip-code level, I assign each zip code the per-capita income of its county. If zip code include parts of multiple counties, whichever county contains the highest population of residents living in the zip code is considered to be the county in which that zip code is located.

In all logit models, I only include stores that have at least 4 quarters of data. For logit models including post-2009 store-level revenue as an explanatory variable, only stores that were observed for at least 3 quarters after 2009 are included.

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