The Effect of Franchising on Store Performance: Evidence from an Ownership Change

Ackermann, Jeff

University of North Carolina at Chapel Hill

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Abstract

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. 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 next create a structural demand model which uses consumer and store locations to predict alcohol sales for all liquor-selling bars and restaurants in Texas over a 10-year period. Using this model, I find that franchising an Applebee's store increases its alcohol revenues by 7 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.

1 Introduction

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. However, data limitations and identification issues complicate

*Department of Economics, University of North Carolina at Chapel Hill. E-mail: jeff.ackermann@unc.edu.
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attempts to estimate the effects of vertical structure on firm profitability and consumer welfare. Franchising serves as a case study of these issues. Theoretical work suggests that a franchised (vertically separated) store should outperform a company-owned (vertically integrated) store. Many of these predictions are based on the hypothesis that a franchisee, whose compensation is determined entirely by store profits, will be less likely to cut corners than a manager, whose compensation is typically less tied to store success. This is essentially a moral hazard argument. While this theory is well established, attempts to estimate the effect of franchising on store performance are made difficult by an important selection issue.

I illustrate this selection issue with a simple model of a profit-maximizing franchisor. The model shows that the franchisor will choose to own stores in the most desirable locations and will choose to franchise stores in less desirable locations. While some of the elements of desirability can be observed by the econometrician (e.g. the number of nearby consumers), others likely will not be (e.g. if visiting the store requires making a left turn at a busy intersection). I use the model to show that these unobservable differences can complicate efforts to estimate the effect of franchising. The model also indicates that this potential bias can be overcome if the researcher observes stores that experience an exogenous change in franchise status. By using an event that resulted in several company-owned stores being sold to franchisees, I am able to estimate the effect of franchising on store performance.

Publicly available data allows me to determine store-level alcohol revenues for all bars and restaurants in Texas. I use these revenues as a proxy for store profits. Included among these stores is Applebee's, a national casual dining chain. At the beginning of 2007, there were 93 Applebee's stores in Texas, 33 of which were franchised. A corporate sale during 2007 resulted in every company-owned store being franchised by the end of 2008. Because I observe revenues for these stores both before and after they are franchised, I can provide some evidence about the effects of franchising.

I make three contributions to the literature. First, I provide evidence that firms choose to own stores in the most desirable locations and to franchise stores in less desirable locations. Second, I provide evidence from both a linear regression and a structural model that stores benefit from franchising. Third, I examine how franchising affects competitors and consumers.

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. I next use a linear regression to look for evidence that franchising an Applebee's store increases its revenues. For stores that change ownership, I find that franchising a store increases its revenues by 19 percent. 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 budget. This results in 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 increases its revenues by 7 percent. By comparing this to a counterfactual in which the stores are not franchised, I calculate the effects of franchising on competitors and consumers. I find that about 30 percent of this additional revenue came 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.

Most empirical work looks at the *causes* of franchising. A prominent theory of why a franchised store should outperform a company-owned store is the moral hazard argument mentioned above (Brickley and Dark, 1987; Lafontaine, 1992). A second theory is one of local expertise: a local franchisee is more likely to know important details about their market than a distant franchisor and therefore be better able to customize a store to fit its market (Mathewson and Winter, 1985; Minkler, 1992). These theories lead to predictions of which chains will use franchising and, for a given chain, which stores will be franchised. There is a substantial amount of research testing these predictions.

Bercovitz (1998) finds that businesses that entrust managers with more decisions are more likely to use franchising; this supports the hypothesis that franchising is used to deal with moral hazard. Similarly, Brickley and Dark (1987) find that monitoring costs and potential free-riding problems are important determinants of whether a store is franchised. In examining the locations of new fast food restaurants, Kalnins and Lafontaine (2004) find that franchisee "clustering" is common; franchisees are more likely to be assigned a new store that is geographically close and demographically similar to their existing stores. This supports the hypothesis that franchising is used because franchisees have local expertise in a certain region. Another indication that local expertise is important comes from the observation that, for retailers with both company-owned and franchised stores, the company-owned stores tend to be located near the franchisor's headquarters (Brickley and Dark, 1987; Minkler, 1990). Other papers investigating franchising using firm-level characteristics as independent variables include Lafontaine (1992), Brickley (1999), and Maruyama and Yamashita (2010).

Relatively little empirical research has examined the *effects* of franchising. Kalnins and Mayer (2004) find that local experience by a franchisee is associated with lower failure rates of pizza restaurant franchises. Fuld (2011) finds that franchised pizza restaurants are better able to predict fluctuations in demand. Krueger (1991) finds that franchised stores pay lower wages than company-owned stores. Lafontaine and Slade (1997) and Thomadsen (2005) find evidence that company-owned stores charge lower prices than franchisee-owned stores. These papers use different output measures than I do and do not attempt to account for the endogeneity of ownership.

The rest of the paper proceeds as follows. In Section 2, I provide details relevant to the study of franchised restaurants. In Section 3, I illustrate why endogenous selection of ownership necessitates the use of an instrument. In Section 4, I describe the demand model and explain how individual preferences are aggregated into restaurant revenues. In Section 5, I describe the data and provide reduced-form evidence that franchising a store increases its revenues. In Section 6, I explain how I estimate the demand model. I present estimation results and counterfactuals in Section 7. In Section 8, I conclude the paper with a discussion of the implications of my results and areas for further research.

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.[1] With over 1,800 restaurants and $4.6 billion in annual revenue, Applebee's is the largest casual dining chain in the United States. Casual dining restaurants are typically characterized by moderate prices, full table service, and the availability of a variety of alcoholic beverages. 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,

[1]National Restaurant Association (2016).

Table 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.

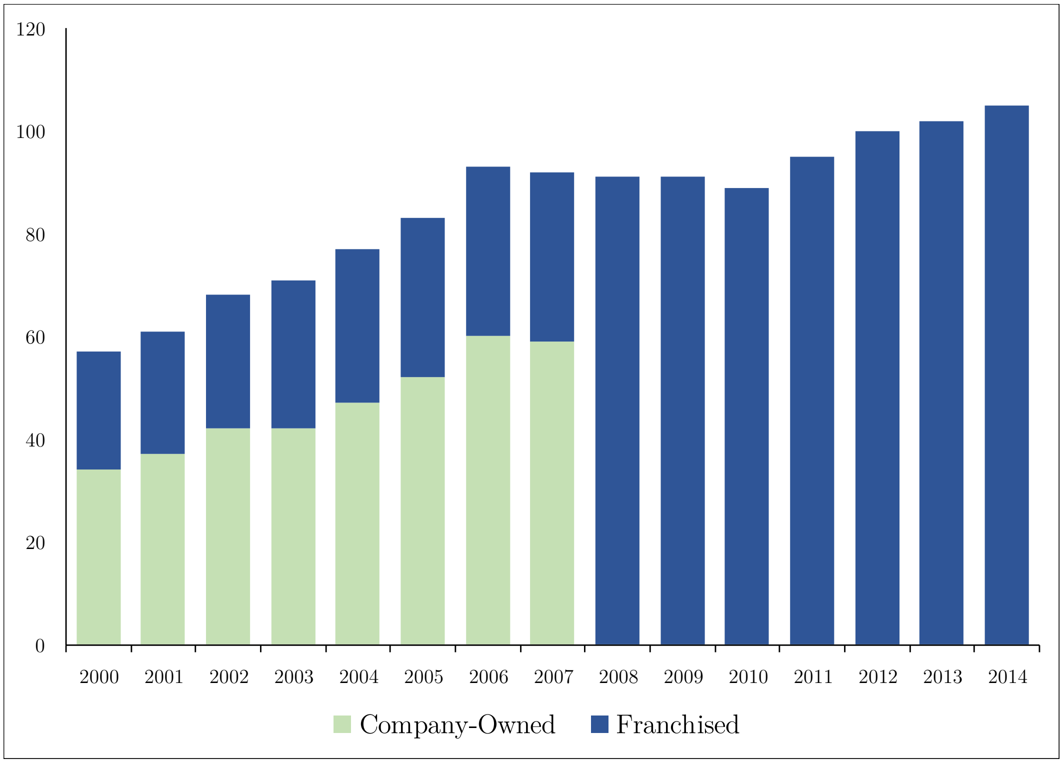
are affiliated with a national chain and have a wide variety of menu items. In addition to traditional American fare like hamburgers and steak, their menus include items inspired by Italian, Asian, and Mexican cuisine. I include the following stores in this grouping: Buffalo Wild Wings, Chili's, and T.G.I. Friday's. Together with Applebee's, these are four of the top seven casual dining chains in the United States. 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.

For the chains that do franchise, fees follow the standard format discussed above and are identical for all stores affiliated with a given franchisor. As shown in Table 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.[2]

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

[2] 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."

Figure 1: Number of Applebee's Stores by Year



the family dining category.[3] 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 of Applebee's stores located in Texas were franchised.[4] Annual store counts by ownership type are presented in Figure 1.

3 Ownership Selection

In this section I construct an illustrative model of a profit-maximizing franchisor deciding whether a given store should be company-owned or franchised. While I do not attempt to estimate this model, I gain intuition from it that I use in my empirical models. The model gives two significant results. First, it predicts that the franchisor will choose to own stores

[3]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.

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

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 is planning to open a store at location j and is deciding 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

$$r_j^C = \sigma a_j + \xi_j, \tag{1}$$

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:

$$\Pi_j^C = r_j^C. \tag{2}$$

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

$$r_j^C < \frac{K + \beta v}{1 - v}. \tag{3}$$

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.[5]

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

$$E[f_j|\xi_j] = E[f_j], \tag{4}$$

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). As shown in (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

$$E[f_{jt}|\xi_j] = E[f_{jt}] \tag{5}$$

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

[5]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 (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.

ownership of a store is uncorrelated with its unobservables.

4 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 6. Consumers are defined by two factors: their income and where they live. All consumers live in the population-weighted centroid of their zip code and have an income equal to the median per-capita income for their zip code. 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:

$$b_{it} = Q_{it} \eta I_{it}. \tag{6}$$

I allow the share of income spent at restaurants to vary by income quartile and define $Q_{it} = [Q_{it}^1,\ Q_{it}^2,\ Q_{it}^3,\ Q_{it}^4]$ as a vector of indicator variables; $Q_{i,t}^q = 1$ 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 that 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 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

$$U_{ijtd} = A_{jt}\alpha + F_{jt}\beta + \gamma H_{jt} + D_{ij}\tau + \epsilon_{ijtd}. \tag{7}$$

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.[6]

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.[7] 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.

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

[6]These examples are not purely hypothetical. As discussed in footnote 2, Applebee's allows for the possibility of a franchisee introducing new menu items. Applebee's stores are also often decorated with local sports memorabilia.

[7]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.

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.[8] 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

$$p_{ijt} = \frac{e^{\bar{U}_{ijt}/\lambda}\left(\sum_{k\in J_t^C} e^{\bar{U}_{ijt}/\lambda}\right)^{\lambda-1}}{\left(\sum\limits_{k\in J_t^C} e^{\bar{U}_{ijt}/\lambda}\right)^{\lambda} + \left(\sum\limits_{k\in J_t^O} e^{\bar{U}_{ijt}/\lambda}\right)^{\lambda}}. \tag{8}$$

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

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

[8] 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.[9]

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

$$R_{ijt} = p_{ijt} b_{it} \tag{9}$$

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

$$R_{jt} = \sum_{i \in Z_t} n_{it} R_{ijt}, \tag{10}$$

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.[10] 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.

5 Data

I next describe the three main 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 2.

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[9] 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.

[10] 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.

Table 2: 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.

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.[11] 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 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 an entire market, rather than only a specific 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 includes 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 higher profit margins than food sales. A second limitation is that the data only includes 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 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.

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

[11] National Restaurant Association, 2016.

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.[12] 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.[13] 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 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.

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

[12] 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.

[13] 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.

stores.[14] I use Applebee's FDDs from 2006 and 2010-2011 to determine which stores were company-owned and which were franchised prior to 2008.

5.1 Reduced-form evidence

Before estimating my structural model, I conduct a pair of analyses. I first use a logit model to predict whether a given Applebee's store was company-owned or franchised prior to 2008. I find that Applebee's chose store ownership based on both observable and unobservable characteristics and that stores with better unobservable characteristics were more likely to be company-owned. Next, I use a linear model with store-level fixed effects to provide evidence that franchising a store increases its revenue.

Endogenous ownership

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 economist, have higher revenue potential were less likely be franchised, as predicted by the model in Section 3. I use a binomial logit model 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.[15] 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 additional demographics and 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

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

[15] 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.

were initially company-owned should have significantly different revenues than those that were initially franchised. 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 my hypothesis that Applebee's chose to own stores in locations with better unobservables.

Further discussion of these models, including definitions of demographic variables and a more detailed discussion of the model that estimates selection on unobservables, can be found in Appendix A. This appendix also includes regression coefficients for a variety of specifications. Results are similar to those discussed here.

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:

$$\log(r_{jt}) = f_{jt}\delta + x_{jt}\pi + \xi_j + \varepsilon_{jt}, \tag{11}$$

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 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 a_{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 conduct several more fixed effects regressions using different control variables; the results are directionally similar and are presented in Appendix B.

6 Econometric Analysis

I now explain how I adapt the model from Section 4 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 4, 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_{jt}^O, 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:

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

Nonlinear least squares estimation produces the estimator

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

where J_t is the union of J_t^C and J_t^A. This estimator is consistent and asymptotically normal. Standard errors are computed by the appropriate transformation of the Hessian matrix.[16]

7 Results

Results for this model are presented as Specification (1) in Table 3. 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. 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.

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

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

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 4.

I find that the sale to IHOP had a positive impact on revenues for Applebee's stores of all ownership structures. This may be due to new chainwide policies, such as new menu items or a new advertising campaign. 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}. Regression results show 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 concerned with 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.[17] 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

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

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 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. 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.

Table 3: 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: (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

7.1 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 4.

I find that franchising increases average store revenue by 7.4 percent. In 2013, average 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.[18]

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 4. 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.

[18]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 4. 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.

TABLE 4: 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.

8 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 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.[19] 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.

Appendix

A Empirical Model of Ownership Selection

This appendix includes results from the logit model discussed in Section 5.1. Results for six specifications are shown in Table 5. Specifications (1) and (6) are discussed in that section, while Specifications (3) through (5) are similar but use different explanatory variables. I now specify the various demographics used to predict the ownership of a store. The first is the logged population of the county where the store is located. The second is the share of the county's population that is non-Hispanic white. This is subsequently referred to as "White". The third is the percentage of the county's population that is employed at a full-service restaurant.[20] This is used as a proxy for how competitive the market is and is subsequently referred to as "Competition". "Revenue" is described in Section 5.1. All models indicate that

[19]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."

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

Applebee's preferred to franchise stores in counties that had low populations, low incomes, more minorities, and more competition.

I next 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

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

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, (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. In all specifications, I find that this estimate is negative and statistically significant with $p < 0.05$. This is an indication that, prior to the IHOP sale, Applebee's preferred to own stores in locations that have better unobservables. This supports the theory raised in Section 3.

B Estimated Effect of Franchising: Linear Model

This appendix contains the results of linear regressions used to estimate the effect of franchising. I estimate the model shown in (11). As was the case in the utility model, I separate the franchising effect into two components to differentiate the franchising effect of 2008 from the franchising effect of 2009 and later.

Table 6 shows the results from regressions using different demographics in a_{jt}. "Population", "Income", "White", and "Competition" are defined in Appendix A. 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 5.1, and Specification (2) is the fixed effect regression described in Section 5.1.

Table 5: 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

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.

Table 7 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 (4). 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.[21] 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 also notable that in most specifications the coefficient on the trend is statistically insignificant.

It is worthwhile to compare the results shown in Tables 6 and 7 with the logit model results shown in Table 5. For example, locations with more competition tend to have lower revenues. Locations with more competition were also more likely to be franchised.[22] 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 thinks that they have a good understanding of the local market or can easily obtain relevant market research, while for a

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

[22] 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.

Table 6: 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. Robust standard errors are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

small town they believe that a local expert will be better able to deal with the intricacies of the market. This is a potential area for further research.

C 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 codes. 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. 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. Distances were calculated using an ellipsoidal model of the earth.

Sample selection

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.

I model quarterly alcohol sales. Mixed beverage tax data is available on a monthly basis, so monthly sales are aggregated for each quarter. Population and income data are available on a yearly basis. I smooth annual changes uniformly over the course of the year.

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.

Table 7: Estimated Effect of Franchising: Comparison of Time Trends

Linear 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. Robust standard errors are in parentheses. "COS trend" is a linear time trend for all stores that were initially company owned. *** p<0.01, ** p<0.05, * p<0.1

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