THREE ESSAYS ON THE RELATIONSHIP BETWEEN FRANCHISING AND PRODUCTIVITY

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The undersigned, appointed by the Dean of the Graduate School, have examined the dissertation entitled:

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a candidate for the degree of Doctor of Philosophy and hereby certify that, in their opinion, it is worthy of acceptance.

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DEDICATION

This dissertation is dedicated to:

My wife, *Kristi*, who has lovingly put up with hour of me working on this research, and has encouraged me every step of the way;

My parents, *Phil* and *Sue*, who inspired me to follow my dreams, and helped to make them a reality;

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Contents

Abstract

This dissertation fills a gap in the literature by exploring the effects of franchising. Much research has been done on the reasons for franchising, but little work has been done on the outcomes from that decision. In essay one, I present a simulated approach to two-stage data envelopment analysis, which is the method I use in essay two. I find that two-stage DEA is a worthy tool for determining efficiency differences between two groups. In essay two, I apply two-stage DEA to US Census Bureau data to determine how franchisee-owned establishments compare with franchisor-owned establishments. I find that franchisee-owned full service restaurants are more efficient than their franchisor-owned counterparts. This is a confirmation of the theoretical franchising literature that suggests that franchising is used to solve an agency problem. In essay three, I examine the causes of changes in the franchisee-franchisor ownership mix within chains. I find that past chain-level efficiency has little impact on future ownership changes. This is also confirmation of previous theories in the literature.

1 Introduction

In 2007 36 percent of restaurants were operated with some franchise affiliation, as either a franchise- or franchisor-owned establishment. Additionally, over a quarter of all restaurants, almost 118,000 of them, were owned by franchisees – quasi-independent business owners who buy into an established chain. According to the Census Bureau, there were 350,947 franchisee-owned establishments in 2007 across all sectors. This accounts for about ten percent of all establishments. All of this is to say that American consumers and corporations have a deep relationship with franchising. It is a very prevalent force within the American economy, and better understanding its effects will provide a better understanding of the economy as a whole. While much research has been done into the reasons for franchising, the optimal structure of the franchise contract, and even the optimal mix of franchisee- and franchisor-owned stores, little work has been done on the outcomes from franchising. This dissertation seeks to make inroads in this area.

Perhaps the preeminent theory for why franchising occurs is to mitigate the principal-agent problem and to align incentives between the owner and the establishment manager (Rubin, 1978; Lafontaine and Blair, 2005). Local managers often have an incentive to increase their own benefit at the expense of the company. This could be by actively working against the corporate office, but more likely is related to exerting a level of effort that is sub-optimal from the corporate office's point of view. For example, a manager might not spend as much time training staff on selling higher-profit menu items. For the company, this is important because it directs customers to the choices that earn the company a higher profit. However, from the manager's perspective, it is extra work that has very little return. If the manager's salary does not increase with the extra work, he or she has little incentive to exert more than the amount of effort required to keep his or her position. By giving the manager an ownership stake in the establishment, the company is hoping to better align incentives. As the owner of the establishment, the franchisee is rewarded with higher profits by working harder. This means that harder work increases profits for the chain and for the franchisee.

All of this sounds great in theory, but the next question becomes the best way to determine how well this theory is working. If owner-managers behave in a way that more closely aligned with the optimal behavior from the chain's point of view, then there should be a metric by which we can measure this success. Profit or revenue may be the metrics that companies use to measure establishment performance, but it is not the desirable metric to use here. Profit, or the difference between revenue and cost, is influenced by too many things that are not under the control of the franchisee. Franchisees do not typically have as much freedom to make decisions on how their establishment is run as an owner of a non-franchised establishment. Many franchisors require franchisees to buy supplies from the company, and require certain procedures to be followed. So if we are interested in seeing how franchisees perform, the best way to do that is to measure how well they perform within the confines of rules dictated to them. In other words, how well do they take the required inputs and turn them into outputs? By measuring how they transform inputs into outputs, essentially a measure of efficiency, we are able to determine whether there is a "value added" from franchising.

This dissertation contains three essays, in which I look at three important aspects of the relationship between franchising and productivity. Essay I lays the groundwork for Essay II. In Essay I theoretically examine the modeling technique that I use in Essay II. By simulating a set of restaurants, I show that two-stage DEA is able to pick up on a known difference between the franchisee-owned establishments and the franchisor-owned establishments. This is a key finding because, while DEA is under-used in the economics literature, is does have some significant benefits over other productivity measures. Unlike marginal or average productivity, DEA is a non-parametric approach, and is able to use multiple outputs. This paper fits more into the DEA and productivity literature than it does in the franchising literature. I use franchising as a vehicle for my simulation, but the application of the findings is widespread. This technique can be useful to any research that is attempting to comparing two groups' efficiency.

Essay II applies the technique explored in Essay I to data from the 2007 Census of Retail Trade (CRT). I compare efficiency at restaurants that are franchisee-owned to restaurants that are franchisor-owned. This contributes to the franchising literature in two ways: the scope of the data, and the uniqueness of the results. As I mentioned above, the franchising literature has not delved much into the effects of the decision to franchise. Part of this problem is likely that data are very hard to come by. Franchise chains are reluctant to give out data for fear that competitors will take advantage of the information. I tried reaching out to multiple franchise chains, and got nowhere. The data that I have for Essay II provides a great advantage not available to other researchers. By using Census Bureau data I have establishment-level data for theoretically every establishment in the United States.[1] The application process was started in January 2013, and I received access in May 2014. I traveled frequently to the University of Minnesota to access the data until the University of Missouri opened a Census Research Data Center (RDC) in November 2015. Other researchers wanting access to this franchise data would need to go through a similar application process, and to my knowledge there are no other active franchise researchers working with Census of Retail Trade data.

Using the Census data I find that franchisee-owned establishments are more efficient than their franchisor-owned counterparts within the full service group of restaurants. For limited service, I do not find significant results. This is likely due to the greater amount of managerial influence within full service restaurants. By giving managers an ownership stake in a restaurant they have an incentive to better train employees or engage in advertising efforts. Since there is simply more training to be done in a full service restaurant, it makes sense that the efficiency difference would be greater for full service over limited service.

Essay III explores a chain-level look at franchising in light of the results from Essay II. If franchisee-owned establishments have superior performance, then why are not all establishments franchisee-owned? There are two streams of research in the area of ownership mix within franchise chains. One area is exemplified by Botti et al. (2009), which looks at performance by ownership mix. They find that mixed ownership leads to the best performance. The other area of the literature is exemplified by Lafontaine and Shaw (2005), which finds that stronger brand value leads to more franchisor-owned stores. Essay III contributes to the franchising literature by combining these two streams of research. I hypothesize that past performance will lead to larger changes in ownership mix. I do this by using two stage least squares to find fitted values for chain performance, and

[1] In practice the number of establishments is much lower. This is because of non-response, missing variable data, and establishments being too small to receive a form.

then use those to predict changes in franchisee ownership. I find that chain-level efficiency has little impact on changes to the ownership mix. I do, however, find that past efficiency has a positive effect on the fee that franchisors charge to new franchisees. I also take advantage of my data and replicate some of the findings in Lafontaine and Shaw (1999), a key paper on franchise contract terms. I find that many of their results are replicable, with some notable exceptions. This is a further contribution to the franchising literature, because it uses current data to replicate widely-cited results that use data from the 1980's.

The rest of this dissertation is laid out as follows: in Section 1.1 I review previous literature on franchising, productivity, and DEA. In Sections 2–4 I present my three essays. I conclude in Section 5 with a summary of my results, and description of my future research agenda.

1.1 Review of the Franchising and Productivity Literature

The topic of franchising has been widely explored in the literature. Researchers have examined how franchise contracts have been set up and how to design the optimal franchise contract. They have also studied how to align incentives of the manager with the owners. In this section, I give a broad overview of the research that has been conducted on franchising. I also give a review of the literature on measuring productivity in retail. After rejecting the some of the more common retail productivity measures, I present a different measure called data envelopment analysis.

1.1.1 The Principal-Agent Problem & Franchise Contract Design

Reducing the impact of the principal-agent problem is one of the primary reasons for implementing franchising. A non-owner manager has a set of incentives that are, at the very least, not perfectly aligned with, and at the worst run counter to, his employer's interests. The manager who receives a set salary has no incentive to go above-and-beyond the basic job description if it involves any more than a minimal amount of work. If his extra work increases company profits, but his salary does not change, there is no incentive to work harder. This problem is exasperated when monitoring costs are high (Affuso, 2002). If a company has stores spread our across a geographically large region, it may be hard for the chain to know what is happening at the local level. Managers who know that they are not closely monitored also know that they can get away with non-profit maximizing activities.

The manager also has an incentive to shirk on his responsibilities to what ever extent he can get away with. This can be mitigated by giving the manager a larger share of the profits through franchising (Lafontaine and Blair, 2005). When the manager becomes an owner, he becomes the residual claimant on the profits from the store he owns, less the royalties that he is required to pay to the franchisor. This means that a franchisee's own utility is much more closely related to the company's profits than a manager's. Unlike a manager, if an owner or franchisee does something that increases profits, his or her income increases.

Once franchising is implemented, however, new agency costs are introduced in two ways. When one corporation owns all stores, all profits go to them. But when stores are franchised, the company is no longer the residual claimant on all of the additional profits from an innovation. This means that just as managers have an incentive to shirk, franchisors have an incentive to free ride off of the franchisees (Lafontaine, 1992). In other words, both parties act as both the principal and the agent. Franchisees rely on franchisors to innovate and develop new products and business practices. Under a typical franchise agreement the franchisee pays the franchisor a start up fee and then pays a certain percentage of sales (or profits) to the franchisor as a royalty payment. Typically, the franchisee also pays a percentage of sales on top of the royalties to help pay for advertising (Lafontaine and Blair, 2005). These royalties and advertising rates pay the franchisor for the services that they provide the franchisees, but they also are designed to provide an incentive to provide new services and products. They also pay for advertising, which should increase demand for all franchisees' products. Since neither the franchisor nor the franchisee receives 100 percent of the profits, there is going to be agency costs.

The second added agency cost is between the franchisees. Since none of the franchisees own the brand that all franchisees are operating under, each franchisee has an incentive to free ride off of good name of the brand (Brickley, 1999). Each franchisee wants to enjoy the benefits of the well-known brand without having to put forth the full effort required to keep that brand name well thought of. The franchisor then has the job of policing the franchisees to make sure that this is not happening. They do this by setting specific standards and monitoring the franchisees. The goal, then, of the franchisee and the franchisor is to find a way to align incentives to minimize these two agency costs.

Franchisors and franchisees are able to align incentives by designing a contract that prescribes certain actions. In a well written franchise contract, both parties are given certain roles (Bhattacharyya and Lafontaine, 1995). The franchisor is able to create an incentive on the part of the franchisee to put forth the right amount of effort. This typically comes from the fact that the franchisee gets to keep all of the profits earned in her store after paying the franchisor a royalty on sales. This should make the franchisee work harder than a non-owner manager would. The franchise contract, according to Bhattacharyya and Lafontaine, is also designed to make sure that the franchisor works hard on the part of the franchisee. The contract should encourage the franchisor to engage in activities that increase sales for the franchisees. Because the franchisor receives a percentage of sales, if sales increase, the franchisor receives more money. Two sales-increasing activities are typically in the purview of the franchisor: advertising and innovation. By advertising, the franchisor is encouraging consumers to visit the local establishments owned by the franchisee. Innovation allows the company to stay competitive against rival firms and keeps customers coming back for new products.

There is an extensive literature revolving around how franchisors set their contract terms. (Bhattacharyya and Lafontaine, 1995) find that franchisors do not increase their royalties as their number of franchisees grows. They present a theoretical model that predicts that the royalty rate charged by franchisors is independent of the number of franchisees. However, they do predict that the franchise fee might change as location-specific information changes. Meanwhile, Mathewson and Winter (1985) argue that the variance in location characteristics is directly related to the variance in royalties. In other words, if all franchisees have very similar locations, there will be very little variance in the royalties that the franchisees pay. However, if the locations have large differences, then different franchisees may end up paying very different royalties.

Additionally, Lafontaine and Shaw (1999) find that franchisors rarely change their fees and royalties. In fact, they present evidence that, while there is significant variation in contract terms, that variation is largely across firms instead of within firms over time. They find that under a simple OLS regression that experience at franchising has a significant impact on royalty rates. However, when they add in firm fixed effects that effect goes away. This suggests that intrinsic differences between firms is the cause of differences in royalty rates and not firm size. This supports the theoretical work of Bhattacharyya and Lafontaine.

Lafontaine and Shaw (1999) also show that there is not a negative relationship between the initial set up fee and the ongoing royalty rates. Theory (e.g. Gallini and Lutz, 1992; Mathewson and Winter, 1985) suggests that the franchise fee and the royalty rate should be negatively related, but this is not borne out in the data. When regressing rates on fees, they attempt to instrument for rates by using a lagged value, but end up rejecting that as an invalid instrument. They conclude that the reason they do not see a negative relationship between fees and royalties is because previous research had misunderstood the purpose of the start up franchise fee. Previous research had assumed that the fees and the royalties were both rent-seeking, and therefore would be negatively correlated; franchisors would either extract rents via the royalty or the franchise fee. Lafontaine and Shaw, however, argue that the franchisee fee is designed to help the franchisor recoup the cost of setting up a new franchisee. In other words, it is a price for a service and not a rent seeking tool.

While it is true that the desire to mitigate agency costs is the motivating factor to design a complete contract, that may not always be possible. Solis-Rodriguez and Gonzalez-Diaz (2012) argue that various factors impact how complete a franchisor's contract is. For example, they show that the degree to which the franchisor-franchisee relationship depends on specific assets will determine the contract's completeness. A much less complete contract is required if neither party has invested in assets that are dependent upon the other party to have value. The party that has a very asset-specific investment will demand a complete contract. Additionally, they argue that franchisors with more valuable brands will require more complete contracts. There is a certain incentive for franchisees to free ride off of the good name of the company and other franchisees. For example, a McDonald's franchisee along the Interstate may have a low incentive to keep his restaurant clean because he knows that a large percentage of his customers are just passing by. Since they will never come in again, and only stopped because they recognized the brand name, the franchisee is not losing future business. Since it would be costly for McDonald's to closely monitor each store, they specify a certain level of service in the franchise contract. Finally, SRGD argue that contractual completeness is determined by the amount of experience that the franchisor has. A company that has been around for a long time knows what needs to be included in a contract, whereas a company that is new to franchising may not know all that is important to include. To test their theories they use survey data from Spanish franchisees. While they get a low response rate, they are able to corroborate their hypotheses.

But all of this is for naught if the expected gain from franchising does not materialize. Franchising as a solution to the principal-agent problem was discussed above, but what exactly is achieved? It can be expected that a business would not sell stores to franchisees if it is not profit-maximizing. Norton (1989) looked at various problems that franchising is designed to combat, such as monitoring costs due to geographic dispersion and the importance of location-specific knowledge. He examines the impact of franchising by looking at how productivity differers between franchised stores and non-franchised stores. He finds that each of his measures of agency costs have a negative impact on productivity, but that franchising mitigates the impact. In other words, the impact is lower across the board for franchised stores than non-franchised stores. Norton uses labor productivity as his measure of productivity because of availability of data.

While there is extensive literature on agency costs and how to align incentives through a franchise contract, Norton's paper is one of only a few that tackle the effects of franchising on outcomes. My dissertation designed to fill that gap. Like Norton, I will be using productivity[2] as my measure of a establishment performance. I use productivity instead of profit for a simple reason: profit is rarely used in franchise contracts as a unit of measure. Franchisees almost always pay royalties off of revenues instead of profits (Rubin, 1978). Rubin suggests that this is the case because controlling

[2] I will use productivity and efficiency interchangeably. This follows the DEA literature.

franchisees is more easily achieved by monitoring revenues instead of profits. This implies that profits are not a good tool for tracking the gains from franchising. So why not use revenue? As I will discuss below, revenue is greatly impacted by demand. It may be the logical unit of measurement for a franchisor to monitor franchisees, but it would introduce too much information beyond the franchisee's control to make it a good measurement here. In other words, a franchisee who has no idea what he is doing may still have high revenues due to being in a good location. Therefore, following Norton's use of productivity allows for the removal of consumer demand and focuses on how inputs are used to generate output.

In the first essay, I explore the utility of two-stage DEA for comparing two groups of establishments. I find that two-stage DEA does a good job of picking up on known differences in efficiency. That gives me confidence that I can use it as a method for comparing establishments in Census data (Essay II) and comparing chains (Essay III). The next chapter contains Essay I, which will detail why DEA is a valid tool for my analysis. Chapters 3 and 4, which contain Essays II and III make use of the tool developed in Essay I.

2 Essay I: Management Differences and Productivity: A Simulated Investigation into Dummy Variables in Two-Stage Data Envelopment Analysis

2.1 Introduction

Following a call by Farrell (1957) for a better measure of productive efficiency, Data Envelopment Analysis (DEA) was first introduced by Charnes, Cooper and Rhodes in 1978. Since they introduced the concept of DEA, their paper has been cited over 20,000 times, has been extended theoretically, and has been applied to a wide variety of applications. DEA was designed to be superior to alternative measures of productivity by allowing for multiple input and output measures (Cook and Seiford, 2009). Frequently used productivity measures, such as partial or total factor productivity, allow only one output to be selected. This is especially restrictive when measuring productivity of entire industries, but also when measuring productivity of firms. Many manufacturers produce various heterogeneous products where using multiple outputs is more illustrative of the production than total sales or a product-by-product analysis. Retail and restaurants, likewise, produce both a physical product and customer service (Betancourt, 2004) or products through multiple channels. DEA has been widely used within the management and operations research literatures. Economists have used DEA to measure productive efficiency of grocery stores (Keh and Chu, 2003), real estate offices (Anderson et al., 1998), hotels (Hwang and Chang, 2003), professional sports teams (Einolf, 2004), general retailing (Donthu and Yoo, 1998), and franchise systems (Botti et al., 2009), among other things.

Reynolds and Thompson (2007) make use of a multi-stage[3] DEA process which examines factors that determine a restaurant's efficiency score (the output from the DEA process). They look at efficiency scores determined using fixed inputs (e.g., wage, seats, square footage), and then use those scores as left hand side variables in regressions to determine how variable inputs (training,

[3]They call it a three-stage process, but the first stage is picking inputs and outputs. I will use the term two-stage in this paper. This is different from two-stage DEA that models a multi-step production process (see: Chen et al. (2009) as an example).

server count and server hours) affect the efficiency scores. They employ this multi-stage approach because it allows them to determine best practices to take to managers. They argue that using the fixed inputs (which they call uncontrollable inputs) reduces the number of objections that managers have to DEA comparisons between establishments. This multi-stage approach is useful in economic research because it uses the efficiency score as a dependent variable in regression analysis, which allows for the exploration of factors that influence how efficient an establishment is. This can be variable inputs, like Reynolds and Thompson use, but can also be other characteristics of interest. However, despite the utility of the approach, it has not been used extensively in economic research. While there has been work done on the two-stage DEA process, I am not aware of any research on the expected magnitude of estimates in the second stage. Even more specifically, I am not aware of any work on the use of binary characteristic variables in the second stage.

This paper attempts to fill this gap by simulating a two-stage DEA process. Specifically, this paper looks at how well the two-stage DEA procedure works when asked to determine how a certain characteristic, which is exogenous to the production function, can influence efficiency. The context used in this paper is the case of franchising because the author intends to use this two-stage DEA process on establishment-level Census data. The purpose of this paper is to show that the method works as intended, while simultaneously extending the two-stage DEA literature. It is not intended to make meaningful conclusions on franchising as an organizational form, but to instead illustrate a use for two-stage DEA. This technique would be useful any time two management practices need to be compared, and is not limited to the franchising question.

The franchising literature predicts that franchisee-owned establishments should be more efficient than their franchisor-owned counterparts (Lafontaine and Blair, 2005). This is because franchisees have a claim on any profits that the establishment generates, whereas franchisor-employed managers do not have this same claim. If a manager works hard to use their inputs (e.g., workers, building, grills, cash registers, etc.) more efficiently, they do not reap any immediate or direct rewards. However, if a franchisee works to better train their employees or make their grill procedure more efficient, their income goes up with their increased profits. Consequently, this theory would suggest that franchisee-owned establishments would be more efficient, ceteris paribus.

On the assumption that this productivity difference exists, I run DEA on a simulated set of establishments. To account for the assumed productivity difference, I randomly designate 75% of the establishments as "franchisee-owned," and then give those establishments a uniform percentage increase in output. I then run DEA on the establishments to obtain efficiency scores. In the second stage, I run a simple OLS model with franchisee-ownership as the independent variable. The franchisee coefficient will shed light on the difference in efficiency score coming from difference in ownership.

In this paper I find that two-stage DEA successfully detects a known difference in output between two groups. The second-stage coefficients are positive and reflect the bonus that was added. This is true even after a series of robustness checks are employed. The paper is organized as follows: In Section 2.2 I give a brief overview of how DEA works. Section 2.3 explains the setup for the simulation procedure, and I present the results in Section 2.4. I test the result's robustness to alternative specifications in Section 2.5 and conclude in Section 2.6.

2.2 Mechanics of DEA

The goal of DEA is to find the best performing decision making unit (DMU) or units in the sample, and then compare all other DMUs to the best performers. The DEA procedure produces an efficiency score for each establishment, or DMU, which gives an indication of how well that establishment performs compared with the best performers. If the establishment is one of the most efficient establishments it is given an efficiency score of 1, and is said to be on the frontier. If the computed DEA efficiency score is 0.75, that tells us that the observed DMU is 75 percent efficient (when compared with the best performers) because they could decrease their input by 25 percent and still get the same output (Charnes et al., eds, 2001).

Mathematically, the DEA procedure solves the following constrained maximization problem (Ray, 2004):

$$\textit{efficiency score} = \max \frac{\sum_{j=1}^{m} u_j y_{jk}}{\sum_{i=1}^{r} v_i x_{ik}} \tag{2.1}$$

$$\text{s.t.} \frac{\sum_{j=1}^{m} u_j y_{jn}}{\sum_{i=1}^{r} v_i x_{in}} \leq 1, \text{ for } n = 1, 2, ..., N \text{ DMUs; } u_j > 0, \text{ for } j = 1, 2, ..., m \text{ outputs;} \tag{2.2}$$

where establishments transforms inputs, x into outputs, y and DEA places weights, u and v to maximize the expression. In plain English, DEA sets each DMUs efficiency score such that it is as high as it can be. It does this by setting weights, u on the outputs and v on the inputs, to maximize the expression. The set weights for DMU i are allowed to be different than the weights for DMU j. This is constrained, however, in two ways. First, the fraction cannot be greater than one. Second, when DMU i's weights are applied to DMU j's inputs and outputs, DMU j's efficiency score is still not allowed to be greater than one. By going through all DMUs and solving this maximization problem, DEA is able to give the most efficient DMUs an efficiency score of one and all others score less than one.

2.2.1 Numeric Example

To demonstrate how DEA works and the effect of a discrete shift in productivity, consider a simple numeric example. In a one-input-one-output model, the efficiency score is calculated as the ratio of the inputs (which is labor) used for that level of output on the frontier to the inputs used by the DMU in question. In Figure 2.1, the best performing DMU is DMU A because it has the steepest line to the origin. Because of this, it receives an efficiency score of:

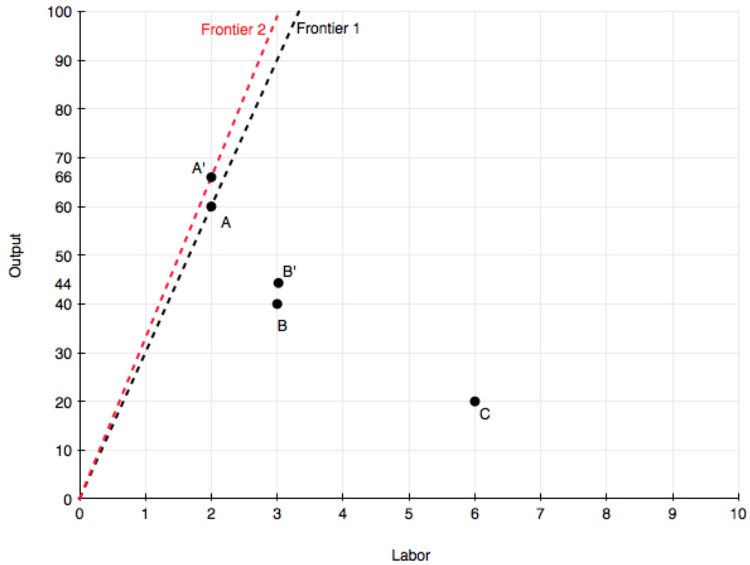
$$score_A = \frac{60}{60} = 1.00.$$

DMUs B and C are not on the frontier, and so they have lower efficiency scores than DMU A:

$$score_B = \frac{40}{99} = 0.4\bar{4}$$

$$score_C = \frac{20}{180} = 0.1\bar{1}$$

Figure 2.1: Example of calculating DEA using fictitious one-input-one-output firms.



Now suppose that DMU B receives a 10% increase in output, unrelated to input choices, making it DMU B′. Because a 10% bonus is not enough to change the frontier, DMU A is still the best performing DMU, and still has an efficiency score of 1.00. Because DMU C did not see a change in its output, and the frontier did not change, DMU C's efficiency score remains $0.1\bar{1}$. DMU B, however, sees an increase in its efficiency score to:

$$score_{B'} = \frac{44}{99} = 0.4\bar{8}$$

After its 10% increase in output, its efficiency score increases by 10%. This shows that a DMU can increase its efficiency score by increasing its output while keeping labor fixed. This makes sense based on DEA's construction because that would be a more efficient use of resources.

Next, suppose that DMU A is the only establishment to see the 10% increase in output, making it DMU A′. Now, because DMU A is still the most efficient DMU, its efficiency score remains at 1.00. This means that when a frontier DMU sees a change in their output, they do not see a corresponding change in efficiency score. This is because efficiency scores are bounded by zero and one, so DMUs are not able to increase their efficiency score, even if they become more productive. The change in DMU A, however, shows up in the efficiency scores of DMUs B and C. DMU B's efficency score falls to:

$$score_{B'} = \frac{40}{99} = 0.\overline{40}$$

similarly for DMU C:

$$score_{C'} = \frac{20}{198} = 0.1\overline{10}$$

For both DMU B and C there is a 9.09% decrease in efficiency score after DMU A increases output by 10%. That is an average decrease in efficiency score of 6.06% (since A′'s efficiency score is the same as A's).

Finally, average product, or partial factory productivity, is a common method of measuring productivity. Because there is only one input, total factor productivity, another common productivity measure, does not make much sense. Here, average products are:

$$AP_A = \frac{60}{2} = 30$$

$$AP_B = \frac{40}{3} = 13.3\bar{3}$$

$$AP_C = \frac{20}{6} = 3.3\bar{3}$$

This gives the same ranking on productivity as DEA gives. When DMU A's output increases by 10%, their average product increases to:

$$AP_{A'} = \frac{66}{2} = 33$$

and the other two DMUs do not see a change in their average product. In this case, a 10% increase in output resulted in a 10% increase in average product for as well. Since there is no frontier in partial factor productivity, this is the same no matter which DMU has a change of output.

2.2.2 Two-Stage DEA

Two-stage DEA is a special application where DEA is first run on the input and output data to generate an efficiency score as above. The second stage uses the DEA-produced efficiency score as the dependent variable in a regression. The goal is to use regression analysis to determine which factors affect the efficiency score, and in which direction. The concept was first introduced by Ray (1991) in a study that examines factors of school productivity. Ray uses inputs such as the number of teachers, support staff, and administrative staff along with outputs of various test scores across 122 school districts in Connecticut. In the second stage regression, he treats the DEA efficiency score as a function of factors that the school district can not control, such as students' socioeconomic status.

A literature using this technique has subsequently grown. Researchers have looked at a multitude of industries using two-stage analysis. Additionally, researchers have looked at the proper modeling techniques to use in the second stage. Common approaches involve Tobit, OLS, and Malmquist indices, among others (Liu et al., 2013). While there has been considerable debate, OLS and Tobit appear to be sufficient for many uses (Hoff, 2007). In fact, despite its seeming perfect application, Hoff finds that Tobit is a misspecification of the second stage model, and that OLS performs comparably to a Papke-Wooldridge specification. This conclusion is verified by McDonald (2009) who finds that OLS is a consistent estimator in the second stage. He argues that since DEA scores are not generated by a censored process, but are instead limited between 0 and 1 by design, Tobit is not appropriate. He also verifies Hoff's result that Papke-Wooldridge provides slightly better results compared with OLS, but argues that the added complexity of analysis does not make Papke-Wooldridge worth while.

2.3 Simulation Procedure

Since the goal of the simulation is to test how well two-stage DEA determines productivity differences between two groups, each simulation cycle consists of three steps: (1) generate establishment-level data, including inputs, outputs, and ownership status, (2) run DEA on the simulated data, and (3) use OLS to determine the efficiency difference between franchisees and franchisors. In order to generate data that are as realistic as possible, I use parameters reported by Ingene (1984). Ingene uses data from the 1977 Census of Retail Trade to determine production functions for a wide variety of retail sectors. For fast food establishments, he uses seats[4] and employment as inputs, and sales as the output measure. He finds that the Cobb-Douglas production function for fast food establishments takes the form:

$$sales_i = 10(employment_i)^{0.65}(seats_i)^{0.23} \tag{2.3}$$

The first step in simulating establishment data using this equation is to simulate input data. Here, again, Ingene provides useful information. He finds that the average fast food establishment uses 94.9 seats and 19.96 employees. He does not provide standard deviations in his summary statistics, but he does provide ranges. I estimate standard deviations of 20 seats and 5 employees by dividing the range by four. Finally, because establishments do not randomly select their inputs independently (e.g., a restaurant is unlikely to have two employees and 200 seats), input values are generated with a set correlation of 0.6 between employment and seats, which is the correlation that Ingene reports.

I randomly assign ownership status to make sure that it is not correlated with input or output. According to Census Bureau reports (2007) about three quarters of franchise-affiliated establishments are owned by franchisees, with 75% of limited service and 69% of full service restaurant sectors being owned by franchisees. In the simulated data, I randomly assign franchisee-ownership to 75% of the establishments. Because of the randomness of ownership, there is no difference, on average, in the generated input data for franchisee-owned establishments and franchisor-owned establishments prior to adding a franchisee bonus.

Once the input data are generated I am able to apply Equation (2.3) to generate output data. The output data generated at this point reflect only the inputs values. The simulation is set up in seven rounds with 1,000 cycles within each round. The rounds represent different efficiency gains for the franchisee-owned establishments, and the cycles each represent a group of 100 establishments on which the DEA is run. The rounds, labeled A-G, are detailed in Table 2.1. These bonuses are

[4] All other industries use square footage instead of seats.

applied using the following equation:

$$sales_{i,j} = \begin{cases} (1+\phi)sales_i, & \text{if } franchisee_i = 1 \\ \\ sales_i, & \text{otherwise} \end{cases} \tag{2.4}$$

where $sales_i$ is the output for establishment i generated in equation (2.3) and ϕ is the designated franchisee bonus for establishment i in round j. For clarity, the outputs generated by Equation (2.4) are labeled OutputA through OutputG.

Table 2.1: Output bonus by round. All numbers are in percentage terms. Group G uses a uniform distribution between 0 and 50 to randomly assign the bonus.

Round	Output Bonus
A	0
B	5
C	10
D	15
E	25
F	50
G	Random: $\mathcal{U}(0, 50)$

The next step is to run DEA on the generated data. In order to check for robustness within my results, I run two different DEA specifications. The first uses seats and employment as inputs. The second specification is modeled after Reynolds and Thompson (2007). As I explained above, Reynolds and Thompson use two-stage DEA to determine how controllable inputs impact efficiency derived from uncontrollable inputs. To implement this model, I also run DEA with seats as the only input and sales as the output.

The final step, and the second stage of the two-stage DEA process, is to estimate the franchisee-ownership effect using regression analysis. This takes the basic form:

$$efficiency_i = \beta_0 + \beta_1 franchisee_i \tag{2.5}$$

where $efficiency_i$ is the efficiency score generated by the DEA step for establishment i and $franchisee_i$ equals one if establishment i establishment is owned by a franchisee. The estimates for β_0 and β_1, along with their standard errors and p-values are collected for each simulation round. I run this regression for both specifications of the DEA.

2.4 Results

2.4.1 Data Simulation and First-Stage Results

Before looking at the second stage results, it is important to examine the initial simulated data. A summary of the inputs generated across all 1,000 simulation cycles is found in Figure 2.2. The two graphs show that there is no difference between franchisee-owned and franchisor-owned establishments for either input. This is to be expected. By design, ownership is random, so ownership has no effect on input levels. This is further confirmed in Table 2.2, which presents test statistics for the difference between franchisee-owned and franchisor-owned establishments on seats and employment. Both test statistics are well below the threshold for significance, confirming that inputs are identical for the two groups. This is important because it confirms that any differences in efficiency found between the two groups must be coming from the bonus added in Rounds B through G.

Figure 2.2: Box plots of input variables seats and employment for franchisee-owned (1) and franchisor-owned (0) establishments. By construction, there is no difference in the inputs between franchisee and franchisor owned stores.

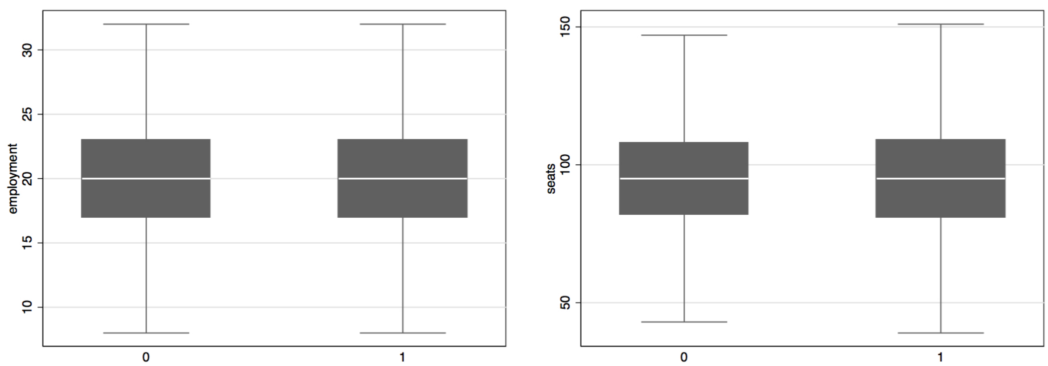
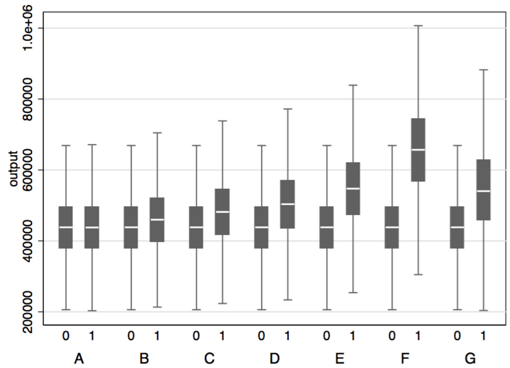


Table 2.2: Input means and standard deviations used in the production function. Difference is the average difference between franchisee-owned and franchisor-owned DMUs. There is statistically no difference in inputs for each group.

Variable	Mean	Standard Deviation	Difference	Std. Err.	Test Statistic
Employment	20	5	0.02	0.04	0.43
Seats	95	20	-0.06	0.15	-0.39

A summary of outputs by round and ownership is found in Figure 2.3. In Round A, there is no

Figure 2.3: Box plots of output for franchisee-owned (group 1) and franchisor-owned (group 0) establishments. The median output is the same in Round A where there is no franchisee-ownership bonus. As the bonus grows in subsequent rounds, the output for the two groups diverges.



difference in output between groups. Since Round A's ownership effect is 0%, this is expected. As the effect grows, the two groups diverge. By Round F, where the effect is a 50% increase in output, the median sales for franchisees is \$654,000 and \$436,000 for franchisors.

The first stage produces the DEA efficiency scores. A graphical summary for the DEA specification using both employment and seats is found in Figure 2.4. The figure provides ranges, quartiles, and median values for the efficiency scores. The DMUs are separated by ownership status, with group 0 being the DMUs that are franchisor-owned and group 1 being the DMUs that are franchisee-owned. For Round A the mean efficiency score for both groups is 0.94. As the bonus increases, the efficiency scores for the two groups start to diverge. In Round F the mean efficiency score for franchisee-owned restaurants is 0.94, and for franchisor-owned restaurants is only 0.63.

Figure 2.4: Efficiency score box plot, for Rounds A through G for franchisees (group 1) and franchisors (group 0). Fewer and fewer franchisors are considered efficient as the bonus grows.

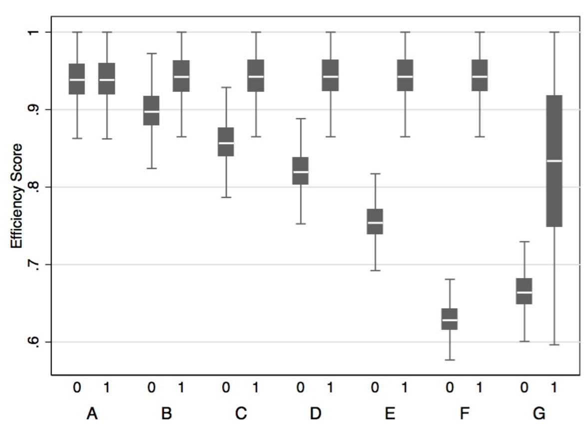


Table 2.3: Percentage of efficient (efficiency score of 1) DMUs owned by a franchisee. DEA Method 1 uses employment and seats as inputs; DEA Method 2 uses only seats. Both use sales as the only output.

	DEA Method 1		DEA Method 2	
Round	Observations	Percent	Observations	Percent
A	4669	0.756	4669	0.757
B	4681	0.932	1002	0.861
C	4635	0.965	1002	0.912
D	4598	0.979	1002	0.950
E	4554	0.992	1002	0.982
F	4528	0.998	1002	0.997
G	4055	0.995	1000	0.991

This leads to the results in Table 2.3. As the bonus grows, an increasing percentage of the efficient DMUs are franchisee-owned. In Round A the percentage of franchisee-owned efficient DMUs reflects the population of establishments almost exactly (75% of the population are franchisee-owned, and 76% of the efficient DMUs are franchisee-owned) in both DEA specifications. Across all simulations, only seven franchisor-owned establishments are considered efficient across all seven rounds. Meanwhile, 1,193 franchisee-owned establishments achieve that status.

Additionally, there are 4,669 establishments that are considered efficient in Round A for the two-input DEA specification. Of those, 3,532 are franchisee-owned, and all of those remain efficient DMUs in subsequent rounds. Within the 1,137 franchisor-owned DMUs in that efficient group in Round A, the mean efficiency score falls to 0.978 in Round B, and all the way to 0.701 in Round F. This shows that the any difference in efficiency score as the rounds progress is due to the franchisee-ownership bonus, and not to any inherent difference in the establishment. For the one-input DEA specification, there are many fewer efficient DMUs for all rounds, except for Round A. However, similar percentages of the efficient DMUs are franchisee-owned.

Finally, efficiency score correlations across rounds are found in Tables 2.4 (all establishments), 2.5 (franchisees), and 2.6 (franchisors). Efficiency score correlations across rounds vary much more for franchisor-owned establishments than those owned by franchisees, which makes sense since there is no bonus for the franchisors. As the franchisees get larger bonuses, the frontier grows, which makes the franchisor's efficiency score go down relative to the franchisees, which stays the same. Generally, correlations are higher for neighbor rounds. For example, between Rounds B and C, the correlation for franchisees is 1.0 and for franchisors is 0.99. However, between Rounds B and G, the correlation is 0.26 for franchisees and 0.74 for franchisors. This gives an indication of how connected efficiency is across rounds. It also gives insight into the number of establishments that have different efficiency scores across rounds. This is important for interpreting the coefficients in the next subsection.

Table 2.4: Correlations for efficiency scores for all DMUs across rounds.

	A	B	C	D	E	F	G
A	1						
B	0.82	1					
C	0.61	0.95	1				
D	0.47	0.88	0.99	1			
E	0.33	0.79	0.94	0.99	1		
F	0.20	0.69	0.88	0.95	0.99	1	
G	0.22	0.52	0.62	0.64	0.65	0.65	1

Table 2.5: Correlations for efficiency scores for franchisee-owned DMUs across rounds.

	A	B	C	D	E	F	G
A	1						
B	0.97	1					
C	0.96	1.00	1				
D	0.95	1.00	1.00	1			
E	0.95	1.00	1.00	1	1		
F	0.95	1.00	1.00	1	1	1	
G	0.25	0.26	0.26	0.26	0.26	0.26	1

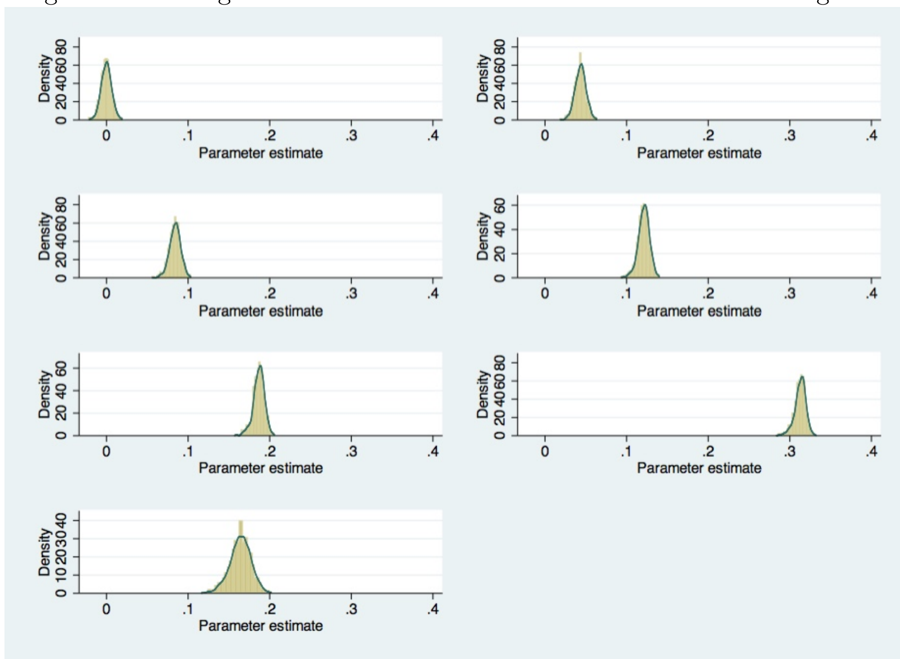
Table 2.6: Correlations for efficiency scores for franchisor-owned DMUs across rounds.

	A	B	C	D	E	F	G
A	1						
B	0.95	1					
C	0.92	0.99	1				
D	0.90	0.98	1.00	1			
E	0.87	0.95	0.98	0.99	1		
F	0.84	0.92	0.95	0.97	0.99	1	
G	0.66	0.74	0.77	0.79	0.81	0.82	1

2.4.2 Second-Stage Results

Results from the second stage of the two-stage process can be found in column 1 of Table 2.7. Histograms of the estimates for β_1 are in Figure 2.5. These histograms are for the regressions using DEA method 1. Histograms for DEA method 2's estimates are virtually identical, so they are omitted. For Round A, with no franchisee bonus, the estimated β_1 is zero. This shows that there is no measurable productivity difference based on ownership, consistent with the simulation assumptions.

Figure 2.5: Histograms for estimated coefficients for each round using DEA.



The estimate for Round B, 0.044, suggests that franchisee-owned DMUs have efficiency scores that are, on average, 0.044 points more efficient. Since the top efficiency score is 1.00, for 100% efficient, then an estimate of 0.044 says that franchisee-owned DMUs are 4.4 percentage points more efficient than their franchisor-owned peers. The average t-statistic across all simulations is 6.99, meaning that the coefficient is, on average, highly significant in all simulations.

As the bonus increases in subsequent rounds the average estimate for β_1 also increases, as does the average t-statistic. When the bonus is 10% in Round C, the average coefficient is 0.08. In round D, with a 15% bonus, the average coefficient is 0.12. Similar results are found in Rounds E and F, with average coefficients of 0.19 and 0.31, respectively. In Round G, where the bonus is on a uniform $[0, 0.5]$ distribution, making the average bonus 0.25, the average coefficient is 0.16. Interestingly, the average estimated coefficient is lower in Round G than in Round E. Both have a mean bonus of 25%, but because Round G has a non-zero variance in the bonus, the average estimated effect is lower. It is also much less statistically significant.

Table 2.7: Coefficients for each specification. T-statistics are in parentheses. All coefficients are statistically significant at the 1% level, except for in Round A, where none are significant at any level.

	1	2	3	4	5	6	7	8	9
Includes Employment in DEA	✓	✓	✓	✓					✓
Includes Seats in DEA	✓	✓	✓	✓	✓	✓	✓	✓	✓
Second-Stage Specification	Linear	Linear	Logged	Logged	Linear	Linear	Logged	Logged	Tobit
Controls	None	Inputs	None	Inputs	None	Inputs	None	Inputs	Inputs
A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0%	(-0.01)	(-0.01)	(-0.01)	(-0.01)	(-0.01)	(-0.02)	(-0.01)	(-0.03)	(0.00)
B	0.04	0.04	0.05	0.05	0.04	0.04	0.05	0.05	0.04
5%	(6.99)	(23.93)	(7.14)	(29.54)	(6.99)	(11.91)	(7.14)	(12.65)	(23.73)
C	0.08	0.08	0.09	0.09	0.08	0.08	0.09	0.09	0.08
10%	(13.41)	(44.00)	(13.85)	(55.15)	(13.41)	(22.57)	(13.85)	(24.42)	(43.56)
D	0.12	0.12	0.14	0.14	0.12	0.12	0.14	0.14	0.12
15%	(19.36)	(62.46)	(20.23)	(79.17)	(19.36)	(32.37)	(20.23)	(35.52)	(61.76)
E	0.19	0.19	0.22	0.22	0.19	0.19	0.22	0.22	0.19
25%	(30.16)	(95.19)	(32.21)	(124.70)	(30.16)	(50.10)	(32.21)	(56.36)	(93.97)
F	0.31	0.31	0.40	0.40	0.31	0.31	0.40	0.40	0.31
50%	(52.06)	(154.85)	(58.52)	(226.00)	(52.06)	(84.27)	(58.52)	(102.25)	(152.44)
G	0.16	0.16	0.21	0.21	0.16	0.16	0.21	0.21	0.17
Random	(7.77)	(8.01)	(8.28)	(8.59)	(7.77)	(7.90)	(8.28)	(8.47)	(7.98)

For the alternative specification in the DEA stage, where seats is the only input used in the DEA, results are very similar to those presented above. The estimated franchisee ownership effect coefficients are found in column 5 of Table 2.7. They are very much in line with the coefficients found in the other specification. This suggests that, at least in the simulated data, the specification of DEA is not overly important. Similar results can be found with similar but different DEA specifications.

The average estimate for β_1 is not exactly equal to the bonus for any of the rounds, except for Round A. Recall from Section 2.2 that there are three possibilities for the change in efficiency score depending on which establishments are moving. This will impact the average effect attributed to ownership status across all regressions. Additionally, a franchisee on the frontier has the same efficiency score as a franchisor on the frontier, despite the fact that the franchisee received the added bonus. The upper limit on the efficiency score is 1.00, so no difference shows up between two establishments.

This suggests that the estimated coefficient should be considered a lower-bound on the true effect. This is represented in Figure 2.6. For example, when the true effect is 5%, the estimate for β_1 shows a 4.4 percentage point difference. The results here do not provide a constant conversion factor, but since all rounds give lower estimates than the true values, it is valid to interpret the coefficients as the lower end of the true value.

Figure 2.6: Graphical representation of the true bonus amount compared with the estimated coefficients for Rounds A-F.

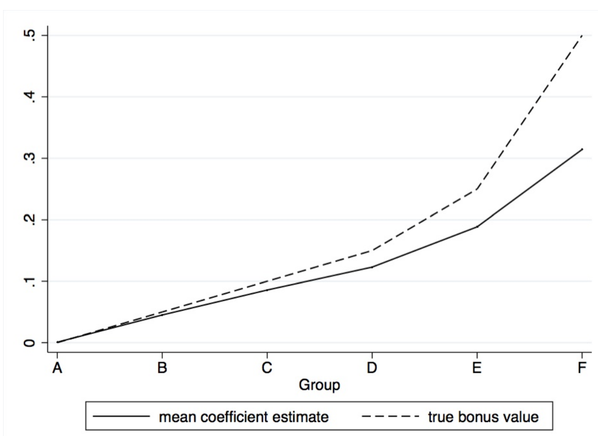


Table 2.8: Average product of labor and capital for each round, the estimated coefficient on the franchisee variable, and the estimated effect at the mean value of average product. All estimated coefficients are statistically efficient except for Round A for both labor and capital, and Round B for capital.

Round	AP_ℓ	β_1 estimate	$\frac{\beta_1}{AP_\ell}$	AP_k	β_1 estimate	$\frac{\beta_1}{AP_k}$
A	22233.38	9.53	0.00	4467.89	-6.22	0.00
B	23089.45	1121.32	0.05	4847.54	227.10	0.05
C	23945.52	2233.10	0.09	5027.20	460.42	0.09
D	24801.58	3344.10	0.13	5206.86	693.74	0.13
E	26513.72	5568.45	0.21	5566.18	1160.38	0.21
F	30794.05	11127.36	0.36	6464.47	2326.98	0.36
G	26498.22	5548.56	0.21	5562.29	1155.39	0.21

2.4.3 Comparison to Average Products

In addition to the DEA efficiency scores, I also compute the average product of labor (AP_ℓ) and average product of capital (AP_k). These are defined as sales divided by labor and capital, respectively. Unlike DEA, average product is not contained to a zero to one range. This means that the estimate for β_1 is not directly comparable to the other estimates. Estimates for AP_ℓ and AP_k are found in Table 2.8. These estimates, like those for DEA, show that a statistically significant difference is detected for franchisee ownership for rounds B to G.

To make sense of these estimates, I divide the estimate by the mean average product. This gives an estimate of how much more productive an average franchisee-owned establishment is than an average franchisor-owned establishment. At the mean average product level for each round, the estimate for β_1 is consistently in line with the DEA estimates.

This is an important conclusion. Average products are a very commonly-used measure of productivity within the economics literature. Papers within economics that use DEA instead of average product needs to account for that departure. This paper shows that the results using DEA efficiency scores and average products are very similar for this application. While average product works well in cases where output per worker or per piece of capital is illuminating, then average product might be the best productivity measure to use. However, there are plenty of cases where average product is too one-dimensional. In the franchising cases here, the use of labor is only one facet of the establishment's productivity. Because I am trying to measure how effectively the manager uses all inputs, average product is too limited. DEA allows for the use of multiple inputs, giving a broader view of the establishment's productivity. So when multiple inputs are important to the analysis, DEA provides that with similar results.

2.5 Robustness Checks

To check the robustness of the results, I run multiple alternative specifications. I first use logged efficiency scores in the regression step. Second, I use inputs as control variables in the regression step. Finally, I use Tobit regressions instead of OLS.

2.5.1 Non-Linear Regression Specification and Control Variables

The first modification to the basic model is to substitute log-transformed efficiency scores as the LHS variable in the second stage. This takes the form:

$$\ln(\mathit{efficiency}_i) = \beta_0 + \beta_1 \mathit{franchisee}_i \tag{2.6}$$

This is a reasonable change because it modifies the meaning of β_1. In the linear specification, β_1 is a percentage-point change in the efficiency score for franchisee-owned establishments. In the logged specification, β_1 becomes a percentage change. Therefore, franchisee-ownership can have a different magnitude effect on less efficient DMUs than on more efficient DMUs. The results are in the third column of Table 2.7. The estimated coefficients are of similar magnitude as the linear specification. At the mean efficiency score, there is little difference between the linear and logged model.

I then add control variables, in the form of employment and seats, to the second stage regressions. This takes the form:

$$\mathit{efficiency}_i = \beta_0 + \beta_1 \mathit{franchisee}_i + \beta_2 \mathit{seats}_i + \beta_3 \mathit{employment}_i \tag{2.7}$$

Because the construction of the simulation prevents any statistical differences in the inputs between the two ownership groups, controls provide a measure of ownership effect, holding the inputs constant. As can be seen in the second and fourth columns of Table 2.7, there is no difference between the models with and without controls. This is true for both the logged specification and the linear specification. This result should not be surprising because the inputs are statistically identical. Therefore, the only difference is coming from the franchisee bonus, which is being picked up by the franchisee variable.

I also add employment as a control variable in the second stage when seats is the only input. Results are found in column 6 of Table 2.7. Once again, there is little notable difference in the results when compared with the results in other specifications. This is especially true when comparing with the results from equation 2.7, which also uses control variables.

2.5.2 Tobit

While there is some debate within the two-stage DEA literature (see Section 2.2.2), many empirical researchers use Tobit as their second stage specification. Because of this, I run the second stage as a Tobit specification to compare with the OLS results. Column 9 of Table 2.7 presents Tobit estimates. This is a two-limit Tobit with an upper limit of 1 and a lower limit of 0. The inputs are used as controls in the second-stage regression. This is a logical, and often used, second-stage specification because of the limits it imposes on the dependent variable. Similar to McDonald (2009) and Hoff (2007), no differences are found in the estimates for any of the rounds, and no substantive differences are found in the t-statistics. The correlation between the OLS (with controls) and Tobit is above 0.99 for all seven DEA specifications. This gives added weight to the argument that there is no clear benefit to Tobit over OLS for the second stage.

2.6 Conclusion

This paper presents evidence that two-stage DEA is a useful tool for determining productivity differences between two groups. In the basic model, which uses seats and employment as inputs and sales as output in the DEA step, and a linear efficiency score and no controls in the regression step, the franchisee-ownership effect is found to be 0.044 when a 5 percent bonus is used. Since the efficiency score has a range between 0 and 1, this suggests that franchisee-owned establishments are 4.4 percentage points more efficient than franchisor-owned establishments. Similar results are found for ownership bonuses of 10%, 15%, 25%, and 50%. In all cases, the estimated coefficient for franchisee-ownership is lower than the actual franchisee bonus.

Since the detected effect is less than the actual effect, I also test a number of alternative specifications. I find no substantive differences in the results when I used logged efficiency scores, when I control for employment and seats, or when I use seats as the only input in the DEA step. There is also little difference found between OLS and Tobit. Perhaps more interestingly, the results are also largely unchanged when DEA is substituted for average product of labor or capital.

The results in this paper suggest that DEA can be successfully employed to determine differences in productivity between two groups. Because of the similarity between the results with DEA and average products, there is not a clear favorite between the two. Therefore, for applications where DEA would otherwise make sense, it can still be used to determine differences between groups. The primary case where this is true is when there are multiple valid outputs. For example, if data on sales and customer satisfaction are both available, DEA allows for both to be used. In traditional measures, only one can be used. Finally, the results suggest that the estimated coefficient on the franchisee-ownership dummy variable should be interpreted as a lower-bound on the actual franchisee-ownership effect. In all of the various specifications the coefficient is lower than the true value, which is in part because of the nature of the DEA frontier. Therefore, when real-world data are being used, the effect that is found is likely to be lower than the true value. This is especially true when the effect is large.

3 Essay II: The Motivated Manager: A Census Data Investigation into Efficiency Differences Between Franchisee and Franchisor-Owned Restaurants

3.1 Introduction

[5] Franchises are everywhere in the American economy. From eating at a fast food restaurant, to buying a car, to getting a hair cut, franchisees operate many of the stores and restaurants that American consumers frequent. These businesses are not just multi-national corporations, but also a local person's small business. There are many reasons why a small business owner would choose to open a McDonald's or an H&R Block instead of their own fast food or tax shop. Perhaps they want to be handed a business plan that is ready to go. Or perhaps they want the name recognition that franchisors offer. No matter the reason, franchisee-operated establishments accounted for about eight percent of all business in the 2007 Census of Retail Trade (Census Bureau, 2007). Including franchisor-operated businesses increases the percentage to about 10 percent.

One suggestion in the literature is that franchising aligns incentives (Rubin, 1978; Lafontaine and Blair, 2005). The classical principal-agent problem is a real concern for multi-unit retail, dining, or sales operations. The objective of the corporate office may be quite different than that of the local manager. A manager who runs a local branch of a chain has very little incentive to innovate or to increase sales (or profit) above the minimum threshold necessary to keep his or her job. As long as his or her job is secure, any improvement above the baseline goes unrewarded since the owner is the sole beneficiary of the additional profits. Franchising is often viewed as a solution to this incentive alignment problem. By selling the location to a franchisee, the corporate office insures that the manager-turned-owner is working to maximize profits. An increase in profits is no longer good solely for the company, but now also benefits the franchisee.

[5] Any opinions and conclusions expressed herein are those of the author and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. Support for this research at the Minnesota RDC from NSF(ITR-0427889) and at the University of Missouri Research Data Center is also gratefully acknowledged. I am also grateful for the comments from seminar participants at the Center for Economic Studies at the Census Bureau for their helpful comments. All errors are my own.

This paper seeks to deepen the understanding of how franchising impacts the actions of the manager. If companies, in fact, use franchising to mitigate the principal-agent problem, then establishments that are franchisee-owned should see higher sales, higher profit, and/or higher productivity. I, therefore, hypothesize that franchisee-owned establishments can be shown to be more efficient. Using data from the 2007 Census of Retail Trade, I use data envelopment analysis (DEA) to determine how efficiently establishments transform their inputs into outputs. I then use regression analysis to examine how franchisee-ownership impacts these measures of productivity. Focusing on the restaurant industry, a much stronger, and more significant franchisee-ownership effect is found in the full service sector (i.e., sit down) than in limited service (i.e., fast food). I also find that these results are robust to various modeling specifications. I suggest that this is because of the difference in task programability between full and limited service. There is a stronger effect for full service because there are more opportunities for an owner-manager to make a difference.

While I save most of the franchising literature review for the introduction to this dissertation, Section 3.2 contains a review of the literature surrounding the tools for measuring productivity in retail, as well as a summary of data envelopment analysis. Section 3.3 presents the analytical tools used, while Section 3.4 outlines the Census data that are used in this paper. Section 3.5 presents the results from the models and Section 3.6 summarizes the findings.

3.2 Literature on Productivity

In trying to show that there is a difference between franchisee-owned and franchisor-owned restaurants, it is vital to accurately measure each restaurant's productivity or efficiency. While there have been numerous papers written on the topic of measuring productivity in retail, a commonly agreed upon measure has proven to be elusive (Achabal, Heineke and McIntyre, 1984; Reynolds and Thompson, 2007). In this section, I will examine some of this literature, detailing the more common measures. I conclude the section with a discussion of an alternative method for measuring productivity, data envelopment analysis.

The most commonly used method is to compute a ratio of some measure of output to some measure of input. Typically this takes the the form of sales, revenue, or transactions divided by employees, payroll, or square feet (Reynolds and Thompson, 2007), creating a partial-factor productivity. It is popular because it is very easy to compute, and the data are relatively easily available. There is also a certain appeal because of its similarity to marginal productivity. For this reason, many companies use this measure to evaluate stores. This approach works well if the research question is dealing with a particular input. For example, partial factor productivity works well to determine how a change in technology impacts worker productivity. When the question is addressing the entire establishment then using partial factor productivity provides only part of the whole story.

Another problem is measuring output for a retail establishment. This comes from the fact that retail establishments are selling an "extended" product (Achabal et al., 1984; Betancourt, 2004). When a consumer buys a product from a retailer, he or she is buying both the physical product as well as customer service, the ability to touch and see the product, and the shopping atmosphere among other things. This means that a simple employees-in-sales-out is not a good measure because the physical product is not the only output from the transaction. An improvement over the partial factor productivity discussed above is to use total factor productivity (TFP) (Reynolds, 1998). Reynolds provides examples for the best way to compute total factor productivity for various industries. In general, he uses revenue (minus sales tax) as the output in the numerator and divides that by a sum of all costs in the denominator as a measure of inputs. He argues that this is a better way of measuring productivity because it encompasses all of the various inputs that the firm uses. Unlike using the number of employees, which only measures output per worker, total factor productivity gets a measure of output per dollar spent.

If total costs for the establishment are not available, then quantities need to be weighted in some way. Total factor productivity calculates weights by finding the regression line through the inputs. Using the residuals from that regression equation, TFP measures productivity by comparing each establishment's performance to the average establishment's performance (using that establishment's inputs). This requires the assumption that all establishments place the same value each of the inputs. This assumption is required because a common weight needs to be chosen for each input

(Metters et al., 1999). It is quite possible that different locations, even from the same company, use different inputs in different ways.

Data envelopment analysis (DEA) is a tool designed to deal with this problem. It still creates a ratio of outputs to inputs, but it does so without requiring that prices or input weights be specified. DEA is a linear programming technique that allows for multiple inputs and outputs (Donthu and Yoo, 1998; Metters et al., 1999; Ray, 2004). The linear programming behind DEA starts with the best performing (or more efficient) stores and then forces all other establishments' efficiency scores to be lower. This means that the DMUs are compared with the best-performing units instead of the average unit.[6]

DEA has been used in many studies examining the relative productivity or efficiency of retail establishments. Joo et al. (2009) use DEA to examine productivity of coffee shops in the Seattle, WA area. They use a few different model specifications in order to pinpoint places of inefficiency within the coffee shops. They use only financial data, which they point out as a weakness of their paper.

Hwang and Chang (2003) used DEA to calculate the efficiency of hotel chains in Taiwan. They use a combination of financial and physical measures for inputs and outputs. Their input measures included the number of rooms, number of employees, and operating expenses. Their output measures are revenue from rooms, food, and other. They also employ a special technique to determine how productivity changes over time.

Keh and Chu (2003) use DEA to measure performance in the grocery industry. Using data from an undisclosed American grocery chain, the authors measure inputs as capital and labor and outputs as accessibility, assortment, assurance of product deliverability, availability of information, and ambiance. They argue that these outputs capture all of the things that the grocery stores are actually selling. As was discussed above, a grocery store is not merely selling groceries; they are selling groceries extended with customer service, ambiance, etc.

Reynolds and Thompson (2007) use DEA to compare productivity in restaurants. They argue

[6] A numeric example, along with more detail is found in Essay I.

that only inputs that are beyond the control of the manager in the short run (such as location or the number of parking spaces) should be included in the analysis. They then take the efficiency score generated from the DEA process and use it as a dependent variable in regressions. The independent variables in these regressions are the controllable inputs. This allows the authors to examine how controllable inputs determine a store's efficient use of uncontrollable inputs.

Finally, Botti, Briec and Cliquet (2009) use DEA to examine how franchising impacts chain-level productivity of French hotel chains. They use DEA to determine that French hotel chains that employ a mix of franchisee and franchisor-ownership are more efficient than chains that have a single ownership type. While this is similar to my work here, I depart from Botti et al. in two significant areas. First, they are using chain-level data instead of establishment-level data. Establishment-level data allow for a much more robust analysis because of the larger degree of variation. Second, they do not conduct second-stage regression analysis. They use a Kruskal-Wallis test to determine differences between organizational types, but they do not employ regression analysis. These two factors make this work a significant step beyond where they ended.

3.3 Empirical Methods

The empirical method used in this paper is two-stage DEA, in which a DEA efficiency score is computed in stage one, and then that efficiency score is used in stage two as a dependent variable. That allows for an examination of the determinants of the efficiency score, including franchisee-ownership. A much more detailed explanation of two-stage DEA can be found in Essay I.

In this paper, I break the sample into two logical subsectors: limited service (fast food) and full service (waiter service). I then compute two efficiency scores for each sample. The first efficiency score comes from a DEA specification with multiple outputs. For limited service, these outputs are sales from the drive thru, sales from counter service (ordering at a counter and taking the food to a table), and sales from takeout. For full service, the outputs are sales from takeout and sales from waiter service. All of these are in dollars. Multiple outputs are a key distinctive feature of DEA that can not be done with more traditional measures of productivity. The advantage here is that it controls for different types of establishments. Establishments that have very few seats may look very efficient, but that is corrected when sales are split between takeout, counter, and drive thru sales. Now a restaurant that has few seats and no counter sales but good takeout sales doesn't look more efficient compared with a restaurant with the same dollar amount of sales, all of which come from counter service, and has a large number of seats. The second DEA specification uses total sales as the output, in dollars.

In all DEA specifications the inputs are payroll, age of the establishment, and the number of seats. Payroll represents the level of employment at the establishment. Age represents the institutional knowledge that the establishment has built up over time. Seats represents the amount of capital that the establishment has. Together, these three inputs cover a wide range of the resources that the establishment has at its disposal to generate output. A more detailed explanation of the variables is saved for Section 3.4.

The output from the DEA becomes the dependent variable in the second stage. In this stage, I run the following regression:

$$\Theta_{i,j} = \beta_0 + \beta_1 \mathit{franchisee}_i + \mathbf{X}_i \delta + \gamma \tag{3.1}$$

where Θ_i is the calculated efficiency score from DEA specification j for establishment i, $(\mathit{franchisee})_i$ equals one if firm i is owned by a franchisee, $\mathbf{X}_i$ is a vector of establishment characteristics that can take various forms (e.g., whether it has a drive thru or how many establishments its owner owns), and γ is a vector of chain fixed effects to control for differences across chains.

If the agency theory of franchising is correct, then I would expect β_1 to be positive. This would signal that establishments that are franchisee-owned have higher efficiency scores than franchisor-owned establishments. Additionally, the magnitude of β_1 shows how much more efficient the average franchisee-owned establishment is over the average franchisor-owned establishment. If the estimate for β_1 is negative, that would signify that franchisee-owned establishments are less efficient than their franchisor-owned counterparts.

3.4 Data

The data come from the United States Census Bureau's 2007 Census of Retail Trade (CRT). The CRT is conducted every five years, in years ending in 2 and 7. As part of the larger economic census, the CRT covers all retail and restaurant establishments. In order to narrow the scope of the data, I limited the sample to establishments in the full service (NAICS code 72211) and limited service (NAICS code 722211) restaurant subsectors. There are two reasons for this: first, franchising is very common within the food industry, and second, more input data is available for restaurants than for other industries. In 2007, 14 percent of full service restaurants and 59 percent of limited service restaurants were affiliated with a franchise.[7] This means that it is a logical choice for analysis. The second reason is one of convenience. Different types of establishments receive different questions on their survey forms. Restaurants are asked about the number of seats, which provides for an input into production other than the number of employees or dollars spent on payroll.

After being restricted to establishments in full and limited service restaurants, the sample was further restricted to establishments that have a franchise affiliation. On the survey, establishments are asked "was this establishment operating under a trademark authorized by a franchisor in 2007?" Establishments are given three response options: (1) "yes – franchisee owned establishment," (2) "yes – franchisor owned establishment," or (3) "no." All establishments that responded with the third option are dropped. Additionally, some establishments were reported as giving other responses, which are also dropped. This leaves in the sample only establishments that are owned by either a franchisee or a franchisor.

The inputs and outputs used are listed in Table 3.1. The selection of inputs and outputs is somewhat limited within the CRT. The best measure of output is sales. While sales is not ideal, because of its inclusion of price, it still provides a measure of the amount of output generated by the establishment. Sales here are measured in thousands of dollars, and cover all sales from 2007. The CRT also provides data on where sales are coming from. On the response form, establishments are asked for either their dollar sales or the percentage of sales coming from a variety of different

[7] A summary of franchising from the 2007 Economic Census can be found at `https://www.census.gov/newsroom/releases/archives/economic_census/cb10-141.html`

Table 3.1: Summary of the definitions for each input and output variable.

Variable	Type	Limited Service	Full Service Service	Meaning
Total Sales	Output	✓	✓	Total revenue; \$1000's
Drive Thru Sales	Output	✓		Revenue from drive thru; \$1000's
Counter Sales	Output	✓		Revenue from counter service; \$1000's
Takeout Sales	Output	✓	✓	Revenue from takeout; \$1000's
Server Sales	Output		✓	Revenue from a waiter; \$1000's
Payroll	Input	✓	✓	Dollars spent on employees
Age	Input	✓	✓	Years since the establishment was founded
Seats	Input	✓	✓	Number of seats in the establishment
Competitors	Control	✓	✓	Number of competitors in the same zip code
Units	Control	✓	✓	Number of estabs. under the same ownership

areas. Of interest to the analysis here (mostly because they account for a large percentage of sales across all establishments) are sales from drive thrus, counter service, takeout, and servers. For limited service restaurants I use drive-thru, takeout, and counter sales. For full service restaurants I use takeout sales and server sales. By using a full picture of sales and a categorical view of sales I am able to better understand how establishments operate, and better account for differences in establishment type. For example, a fast food establishment that only has takeout and a drive-thru may use employees differently than an establishment that has a large dining room. By using a version of DEA with multiple outputs I can better untangle these differences.

The primary choices for input measures from the available CRT data are payroll, employees, and seats. Seats is defined as the number of seats, including patio and bar seats, within the establishment. Seats acts as a measure of the physical capital available to the establishment. Presuming that most establishments do not want to have large sections of their dining room open without seats, the number of seats is not easily changed by the manager. In other words, the number of seats can serve as a measurement of serving capacity. This is especially true in full service restaurants. With limited service restaurants, it is likely that a significant percentage of business is coming from take-out, delivery, or the drive-thru. However, even with that being true, the number of seats serves as a measure of expected customer volume.

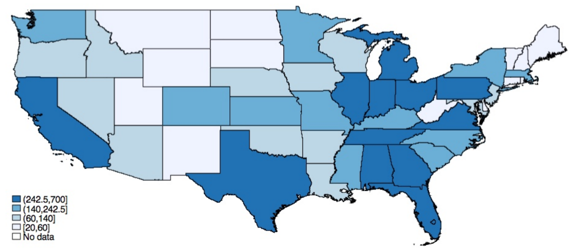
Payroll is measured as thousands of dollars spent on employees during the entire year of 2007. Employment is also a measure of workforce size, but is measured as the number of employees during the week of March 12. This means that employment is a weaker measure of the workforce than payroll because it can be influenced by unique events on March 12. For example, an establishment that opened on April 1 would have positive payroll for 2007, but no employees. I use only payroll in my analysis because of the oddities in the construction of employment. The other reason why payroll is better than employment is because of the high use of part time employment in restaurants. By using payroll, I do not need to worry about whether an employee is full time (and therefore presumably better trained) or part time.

I create a few additional variables from Census responses. The first is a measure of the number of other establishments competing within the same area. It is defined as the number of establishments within the same zip code that share the same line of business. Establishments are asked by Census what type of product they sell most. It makes more sense to limit competitors to establishments in the same line of business than it does to include all food establishments. While a sit down steak restaurants and a fast food hamburger restaurant are both food establishments, they are not competing for customers at the same time. The same people might patronize both establishments, but potential customers are likely not deciding between the two for that night's dinner. The number of competitors is used as a measure of competition, which indicates how much effort is needed to win customers. Much less effort is needed to woo customers when there are no competing firms than if the establishment is on a crowed main street. However, there might also be network effects going on; a large number of establishments might indicate high consumer demand, which could cause higher sales.

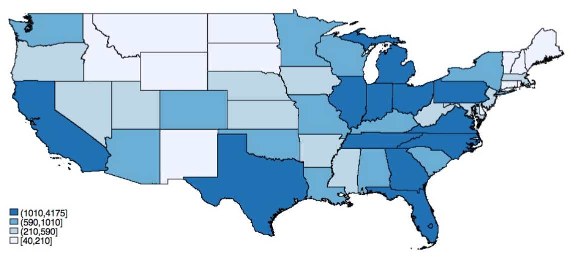
I also create a measure of the age of the establishment, which is defined as 2008 minus the year that the establishment was founded. The data are left-censored in 1976, so the oldest establishments in the data are listed as 32 years old. The age of the the establishment serves as a measure of reputation and learning-by-doing. One of the reasons why companies franchise to to gain access to local information held by the franchisee. The longer the establishment is open, the more local information is gathered. It also serves as a measure of how well known the establishment is in the community. A longer existing establishment has had more time to build name recognition form potential customers.

State fixed effects are computed by using the state that appears for the establishment in the Business Register. Establishments are not evenly spread across the country. The state with the smallest representation in the sample is Alaska in the full service subsector, with only 15 establishments. A visual representation of where establishments are located is found in Figure 3.1.

Figure 3.1: Maps showing where establishments in the two samples are located.



(a) Full Service



(b) Limited Service

I also include Census tract demographic information from the American Community Survey. This data includes the population of the Census tract and the median income. While Census tracts are small, this gives an indication of where the restaurant is located. Higher population and/or higher income shows that the restaurant is in a busy areas instead of along a deserted highway.

Finally, I create a variable containing the number of establishments owned by the same owner. This could be the franchisor, a single franchisee, or a corporate franchisee. While my analysis here treats franchisees as a single owner-operators, that is not always the case. However, the analysis shows that this distinction is not a major concern.

Summary statistics for the inputs and outputs for both full and limited service restaurants are in Table 3.2. Not surprisingly, full service restaurants have higher sales, higher payroll, and more seats than limited service restaurants. On average, both types of restaurants have a similar number

Table 3.2: Summary statistics for the input and output variables.

	Full Service			Limited Service		
Variable	N	Mean	St. Dev.	N	Mean	St. Dev.
Total Sales	8900	1583.21	1023.4	40000	1231.36	708.44
Counter Service Sales	8900	15.26	125.47	40000	502.05	445.59
Drive Thru Sales	8900	41.04	147.94	40000	592.77	216.62
Takeout Sales	8900	180.63	253.84	40000	122.11	231.49
Server Sales	8900	1254.07	982.64	40000	14.28	113.78
Seats	8900	131.01	72.13	40000	69.48	41.01
Years of Existence	8900	14.62	9.96	40000	14.21	9.42
Number of Competitors	8900	28.88	19.42	40000	25.8	18.61
Employment	8900	43.28	24.97	40000	27.75	16.58
Payroll	8900	534.6	374.07	40000	314.02	178.49

Table 3.3: Percentage of establishments in the sample that are franchisee-owned and franchisor-owned.

	Full service	Limited service
Franchisee-owned	65%	78%
Franchisor-owned	35%	22%

of competitors and are the same age. Table 3.3 breaks down the two sectors into the number and percentage of franchisee-owned and franchisor-owned stores. Both sectors are roughly 70 percent franchisee-owned and 30 percent franchisor-owned. This compares well with other documented percentages. Lafontaine and Shaw (2005) report that 78 percent of establishments in their *Franchise 500* data, which is from the 1980's, are owned by franchisors. I find similar results in my replication of Lafontaine and Shaw's findings, which are reported in Eassay III. Additionally, *Nation's Restaurant News* reports that 73 percent of franchise-affiliated establishments in their Top 200 are owned by franchisees in 2014.

Establishment names are important to be able to control for differences between chains. Because each establishment – both franchisee-owned and franchisor-owned – operates within the prescribed rules set forth by the franchisor, the effect of franchisee ownership is likely different between chains. To determine the chain to which an establishment belongs, I use administrative data linked to the CRT. Establishments are asked to provide a name for their establishment, and are given two blanks. One is intended to be a legal name, and the other a "doing business as." However, there is a fair amount of variation in the way responses were given. To get around this, I started with a list of all chains that have appeared in the *Franchise 500* at any point between 2004 and 2014. If either

Table 3.4: Summary statistics on the DEA efficiency scores, which have been multiplied by 100.

	N	Mean	St. Dev.
Full Service, Multiple Outputs	8900	30.88	14.31
Full Service, One Output	8900	27.39	11.76
Limited Service, Multiple Outputs	40000	13.42	8.31
Limited Service, One Output	40000	8.26	3.33

name field contains the name of a known franchise chain, the establishment takes that name. I also add names to the list generated from the *Franchise 500* based on observations of trends in the non-matched data. After searching, and then standardizing, names, about eighty percent of establishments in both subsectors were able to be named.[8]

3.5 Results & Discussion

Summary statistics for the DEA step are found in Table 3.4. These efficiency scores have been scaled up, so the range is between 0 and 100. Recall, for each subsector there are two efficiency scores, one for the DEA specification with one output, and one for the DEA specification with multiple outputs. The mean efficiency score of 30.88 for the multiple output full service specification suggests that the average full service establishment is 30.88% efficient compared with the most efficient full service restaurants in the sample. Because the mean efficiency score decreases as the sample size increases (Zhang and Bartles, 1998), it makes sense that the mean efficiency scores are lower than studies that use very small sample sizes.[9] For both subsectors the mean efficiency score is higher for the multiple output specification. This is because a new output will always increase the efficiency score, on average (just like a new input will always lower efficiency scores, on average).

Results for the second stage, the regression stage, are found across Tables 3.5 to 3.8. Table 3.5 contains the results from the limited service subsector and the multiple output DEA specification. Column (1) shows a positive and significant franchisee ownership effect. However, once chain fixed effects are added in column (2), that effect goes negative. There is reason to believe that the error structure is different across chains, and once I cluster standard errors at the chain level, the

[8] Because of Census policies on disclosure, the matched chains can not be listed.

[9] The mean efficiency score decreases as the sample size grows because the probability of finding a more efficient firm increases as the sample grows. It is not because of anything in the calculation. Establishments are still only compared with the frontier.

Table 3.5: Regression results for limited service restaurants. The dependent variable is the DEA efficiency score computed with multiple outputs (drive thru, counter, and takeout sales). T-statistics are in parentheses. Chain clustering clusters the standard error at the chain level. ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Franchisee	0.95***	-0.91***	-0.91	-0.92	-0.79	-0.78	1.5	-0.98
	(9.5)	(-7.92)	(-0.72)	(-0.72)	(-0.67)	(-0.66)	(1.08)	(-0.8)
Number of Competitors				0	0	0		0
				(-0.09)	(-0.4)	(-0.38)		(-0.4)
Drive Thru Dummy						0.24		
						(0.24)		
Units							0**	
							(1.94)	
Units× Franchisee							0***	
							(-2.68)	
Income								0***
								(2.91)
Population								0***
								(2.22)
Constant	12.69***	10.32	10.32	10.32	11.59	11.4	7.92	9.51
	(143.84)	(0.3)	(0.3)	(0.3)	(0.31)	(0.31)	(0.31)	(0.32)
Chain FE	N	Y	Y	Y	Y	Y	Y	Y
Chain Clustering	N	N	Y	Y	Y	Y	Y	Y
State FE	N	N	N	N	Y	Y	N	N
N	40000	32000	32000	32000	32000	32000	32000	26000

significance goes away in column (3). Regardless of what other controls are added, the estimated coefficients stay very small and insignificant. Other control variables are significant, such as the number of units, but are too small to have a meaningful economic interpretation.

Table 3.6 presents the same regressions as the previous table, but uses the DEA score from the single-output specification. Again, little significance is found. Once standard errors are clustered at the chain level, none of the franchisee coefficients are significant. Taken with the results in the previous table, there is little evidence of a franchisee-ownership effect within the limited service subsector.

In Table 3.7, I present results from the DEA specification with multiple outputs for full service restaurants. For all second-stage specifications, columns (1) to (7), the franchisee effect is positive and significant. This indicates that franchisees make their establishments more efficient than franchisor-employed managers are able to make their establishments. Since the efficiency score is between 0 and 100, a coefficient of 3.0 means that the average franchisee-owned restaurant is three

Table 3.6: Regression results for limited service restaurants. The dependent variable is the DEA efficiency score computed with total sales as the output. T-statistics are in parentheses. Chain clustering clusters the standard error at the chain level. ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Franchisee	0.32***	-0.01	-0.01	-0.01	0	0.01	0.2	-0.03
	(7.92)	(-0.25)	(-0.05)	(-0.05)	(0.02)	(0.03)	(0.5)	(-0.14)
Number of				0	-15	0		0
Competitors				(-0.11)	(-0.82)	(-0.81)		(0.04)
Drive Thru						0.11		
Dummy						(0.43)		
Units							0	
							(0.43)	
Units×							0***	
Franchisee							(-5.67)	
Income								0
								(1.61)
Population								0
								0
Constant	8.01***	6.94***	6.94***	6.95***	8.95***	8.87***	6.75***	6.49***
	(226.44)	(9.29)	(26.35)	(26.32)	(10.57)	(9.92)	(17.15)	(26.73)
Chain FE	N	Y	Y	Y	Y	Y	Y	Y
Chain Clustering	N	N	Y	Y	Y	Y	Y	Y
State FE	N	N	N	N	Y	Y	N	N
N	40000	32000	32000	32000	32000	32000	32000	26000

percentage points more efficient than a similar franchisor-owned restaurant. At the mean efficiency score, that is about a 10% increase in efficiency.

These results are robust to various specifications. In column (1) I do not use any controls. As I add in fixed effects – column (2) – and then cluster standard errors at the chain level – column (3) – the results stay consistent. In column (4) I add in a control for the number of competitors in the area. While that coefficient is insignificant, the franchisee ownership coefficient remains positive and significant. In column (6) I control for the size of the ownership group the establishment is in, whether that is the franchisor, or a multiunit franchisee. This controls for large franchisees, and the effect is very small. And in column (7) I control for demographics of the Census tract. In all of these the effect stays between 1.83 and 4.55, and is significant in all of them.

A very similar pattern emerges for the single output DEA specification. Those results are in Table 3.8. The franchisee coefficient is negative and significant in column (1), but that column does not include any controls or fixed effects, or chain standard error clustering. That means that I

Table 3.7: Regression results for full service restaurants. The dependent variable is the DEA efficiency score computed with multiple outputs (server and takeout sales). T-statistics are in parentheses. Chain clustering clusters the standard error at the chain level. ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Franchisee	1.83***	3.28***	3.28***	3.28***	3.07***	4.55***	3.65***
	(5.86)	(6.39)	(3.07)	(3.09)	(2.69)	(3.37)	(3.56)
Number of Competitors				0.01	0		0.02
				(0.69)	(0.24)		(0.98)
Units						0*	
						(1.67)	
Units× Franchisee						0	
						(-0.81)	
Income							0
							(0.68)
Population							0
							(4.05)
Constant	2.69***	44.62***	44.62***	44.34***	39.22***	43.3***	42.37***
	(115.64)	(17.05)	(41.76)	(42.23)	(12.56)	(32)	(32.42)
Chain FE	N	Y	Y	Y	Y	Y	Y
Chain Clustering	N	N	Y	Y	Y	Y	Y
State FE	N	N	N	N	Y	N	N
N	8900	7100	7100	7100	7100	7100	5500

discount the validity of that coefficient. For all other columns, the franchisee coefficient is positive and significant. Just like in Table 3.7, the estimated franchisee effect is economically meaningful, although smaller than in the multiple output specification. Here, the franchisee effect ranges from 2.26 to 3.02, meaning that franchisee-owned full service restaurants are 2.26 to 3.02 percentage point more efficient than their franchisor-owned counterparts. Again, this is about 10% of the mean efficiency score.

The results presented in Tables 3.5 to 3.8 suggest that franchisees have a stronger impact on restaurant productivity in the full service subsector than they do in the limited service sector. Both results are highly robust to different second-stage specifications. Regardless of what control variables are used, the effect in limited service is essentially nonexistent. For full service, the effect ranges from about two percentage points to about four and a half percentage points.

There might be concern that the two different DEA specifications are modeling essentially the same thing, and therefore they are not really a robustness check of one another. However, that is not true. The correlation between the two DEA efficiency scores for full service is 0.75 and for limited

Table 3.8: Regression results for full service restaurants. The dependent variable is the DEA efficiency score computed with total sales as the output. T-statistics are in parentheses. Chain clustering clusters the standard error at the chain level. ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Franchisee	-0.86***	2.66***	2.26***	2.66***	2.63***	2.29*	3.02***
	(-3.26)	(6.22)	(2.68)	(2.69)	(2.81)	(1.67)	(3.11)
Number of Competitors				0	0		0.01
				(0.25)	(-0.13)		(0.7)
Units						0	
						(-0.3)	
Units× Franchisee						0	
						(1.34)	
Income							0
							(1.18)
Population							0***
							(4.12)
Constant	27.95***	24.99***	24.99***	24.91***	18.47***	25.3***	22.91***
	(132.35)	(11.46)	(25.21)	(25.96)	(5.67)	(18.43)	(20.86)
Chain FE	N	Y	Y	Y	Y	Y	Y
Chain Clustering	N	N	Y	Y	Y	Y	Y
State FE	N	N	N	N	Y	N	N
N	8900	7100	7100	7100	7100	7100	5500

service is 0.66. This is a high correlation, but is not high enough to cause concern that they are essentially the same. These two DEA efficiency scores are getting at the same thing, but are both useful in examining the franchisee-ownership effect. One is narrowing in on sales type, the other is picking up on other types of sales outside of the main categories (e.g., catering).

So if these results are robust, what conclusions can be drawn? And of specific interest: why does full service see a strong franchisee-ownership effect, whereas limited service does not? On the surface, full and limited service restaurants may not seem that different. Both are places where people go to eat meals away from home. However, the operation is very different. In a limited service restaurant, the manager (or franchisee) is supervising employees who are doing very task-programmable jobs. The manager can train an employee to ask about add-on side items or on how to smile and greet a customer, but there is little customer interaction. The same is not true in full service. In a full service restaurant, employees, especially servers, are spending significant amounts of time with the customers. And as a result, their job is much less task-programmable. A good manager has a lot of opportunity to train servers on how to interact with customers.

And this is why franchisee-ownership matters. If the manager does not have an incentive to aggressively increase the establishment's revenues (or profits) they may not take the time to train servers on how to build a rapport with customers that may lead to more drink, appetizer, or dessert sales. The chain is able to give directions to their employee-managers on how to train servers, but a motivated franchisee can make a big difference.

The fact that the estimated effects on the franchisee coefficients are not very large, especially in limited service, means that franchisors are good at determining whether a new establishment should be franchisee-owned or franchisor-owned. Lafontaine and Shaw (2005) find that franchisors keep a steady ownership mix after about seven years, and I confirm this in Essay III. As the chain expands, the franchisor needs to determine whether the next store will be sold to a franchisee, or whether the chain will operate it themselves. Especially with more experience, a talented franchisor will be able to determine whether it is best to sell the establishment or operate it themselves. Franchisees do not own 100% of the restaurants in the sample, and because the franchisors are acting rationally, it must be profit maximizing to keep some restaurants owned by the franchisor. If the franchisor is good at determining which stores should be in which category, then there should be little difference. The fact that there is a positive and significant effect in full service shows that franchisees really do make a difference when management motivation can be a difference maker, such as when higher levels of training are possible.

This is an important contribution to the franchising literature. This is a much larger, and much more comprehensive study that has been done on franchising's outcomes. This is confirmation that the agency theory is accurate in explaining the motivation behind franchising. By franchising the restaurant is able to ensure that the manager has an incentive to work hard. And because I find an effect in the subsector that has the most managerial impact, it is clear that a motivated franchisee can make a difference in the efficiency of the restaurant.

3.6 Conclusion

In this paper I present a two-stage DEA model on the efficiency differences between franchisee-owned and franchisor-owned restaurants in the full and limited service subsectors. I find that there is no noticeable franchisee-ownership effect in limited service. However, I find a strong positive, statistically significant franchisee-ownership effect for full service restaurants. This result is robust to various specification changes. Even after including different control variables, such as the number of units the owner owns, Census tract demographic information, and state fixed effects, I still find a positive and significant effect. This positive effect also holds steady when I switch from a multiple output to a single output specification of the DEA step. This is an exciting finding because it shows that franchisees can make a difference, which is an indication that the agency theory of franchising is correct. I explain the difference between the results for limited service and full service by the level of managerial control in the two subsectors. In the subsector where managers exert more control a larger effect is found. Again, this fits with the agency theory.

Future research can expand on these results. Whereas this is a cross-sectional analysis, similar data are available for 2002 and 2012. By adding these years in, I can create a panel data set to examine how efficiency changes over time. This will be especially of interest for establishments that change ownership type. Additionally, I will combine the Census data with the *Franchise 500* data used in Essay III to look at how contract terms, franchising experience, and distance from the chain's headquarters impact efficiency.

4 Essay III: Expanding the Franchise(d Chain): An Exploration of Determinants of Franchise Contract Terms and Ownership Mix

4.1 Introduction

The franchising literature has been filled by authors attempting to explain the reasons and procedures for franchising. There is much less literature written on the effects of franchising. Some research has been done on the ownership mix between franchisee-ownership and franchisor-ownership, but it has been done on the chain-level or the state-level, or has been done on very small samples. In Essay II, I show that franchisee-owned establishments are more efficient than franchisor-owned establishments in the full service restaurant subsector. If that is true, then why do franchisors not franchise 100% of their establishments? This essay seeks to better understand how the establishment-level conclusions from Essay II can be translated to the chain-level. While establishment-level research is important, chain-level research also has a place. The establishment data are only available from Census on five year intervals. The chain data I use here are available every year. Additionally, I have additional information on contract terms that are not available in the Census data.

In this paper, I connect the literature that examines efficiency differences based ownership mix (e.g., Botti et al. (2009)) to the literature that examines how ownership mix is determined (e.g., Lafontaine and Shaw (2005)). I hypothesize that franchisors look to past efficiency, as measured by data envelopment analysis, when determining how to change their ownership mix going forward. If a franchisor determines that they are under-performing relative to other firms in their sector, they can change their ownership mix to correct for that. This is a novel approach. Previous literature has looked at determinants of ownership mix, such as brand value, but none that I know of have looked at past performance as a determinant. I apply a two-stage least squares approach to this question. In the first stage, I estimate the efficiency score as a function of the percentage of franchisee-ownership, royalty rate, and experience variables. I determine that the number of outlets and the years of experience have a strong, negative effect on the efficiency score. I also determine that the percentage of franchisee ownership has a positive, but insignificant impact on the efficiency score. In the second stage, I use fitted values from the first stage, and find that the fitted efficiency has a small, negative, and insignificant impact on the percentage point change in franchisee ownership.

The data that I use also allow me to replicate Lafontaine and Shaw (1999). I revisit three of their most influential findings with newer data. This is an important contribution to the literature because these findings are so widely cited. Their findings have greatly influenced the franchising literature, but they are from a data set with data from the 1980's, which is before almost all modern information technology. This means that monitoring costs are significantly lower today, and geographic distance is not as important. Seeing how their results hold up is therefore important to the future of the franchising literature.

I start with a review of the literature that I am building off of in Section 4.1.1. I present my methods in Section 4.2, and the data in Section 4.3. I discuss my results in Section 4.4, and conclude in Section 4.5.

4.1.1 Review of the Relevant Literature

There is a small selection of work that has been done on how the franchisee-franchisor establishment mix impacts productivity. Botti, Briec and Cliquet (2009) examine how the percentage of franchisee-owned stores impacts productivity, which they measure using DEA. The dataset that Botti et al. use is a sample of 16 French hotel chains in 1997. Using sales as the output, and costs, territory coverage, and chain duration as the inputs, they find that there is not a statistically significant difference in performance between highly franchised chains, medium franchised chains and low franchised chains. They argue that their results might come from the small sample size, and that future research should take another look using a larger sample.

Piot-Lepetit, Perrigot and Cliquet (2012) also look at French franchisors, but do so with a larger dataset. Of particular note is their use of the percentage of franchisee-owned stores as an input in the DEA. This allows them to analyze how chains should change their franchisee-franchisor mix to become more efficient. The authors find that chains have generally done a good job of setting this mix to be efficient.

In the area of ownership mix, Lafontaine and Shaw (2005) find that the ownership mix is stabilized within chains after about seven years of franchising experience. This result is puzzling because it is only a partial support of the agency theory of franchising. The agency theory suggests that owner-managers will be more apt to run the establishment in a way that is profit maximizing for the chain because they are a residual claimant of establishment profits. As they increase their effort, their income increases. It is, at the same time, a rebuff of the capital theory of franchising, which says that franchisors do not have the needed capital to expand their chains, so they sell new establishments to franchisees who have capital. Once the franchisor has capital built up, they will buy back units from franchisees.

Their results show that franchisors settle on a set percentage of franchisee-ownership, roughly around 80-85%. Even when a franchisor has been established for a long time they do not change this percentage – increasing both types of establishments as they grow. This goes against the capital theory, but it also goes agains a strict interpretation of the agency theory. If franchisees have more incentive, why not franchise 100%? The answer is that franchisors respond to the value of their brand, and keep more company stores as their brand becomes more valuable. This is because franchisees also have an incentive to free-load off of the brand's value. By keeping company stores, the franchisee is able exert more control over the system. It also signals a stronger commitment in the brand to the franchisees.

4.2 Method

In Essay II I show that franchisee-owned full service restaurants are more efficient than their franchisor-owned counterparts. This fits into the chain-level empirical papers discussed above. It is also a confirmation that the agency theory of franchising is correct. However, as I also discuss above, there are reasons why a franchise would want to own some stores themselves, even if there are efficiency gains from franchisee ownership. This paper seeks to understand how and why franchise chains change their ownership mix by combining it with the work on ownership mix efficiency differences.

To do this, I use Botti et al. (2009) as a launching-off point. I start by applying the concepts used in their paper, but to a larger and more diverse sample. While they focused on hotel chains, I use chains from a wide variety of sectors. I start by calculating DEA efficiency scores for each chain in each year using revenue as the output, and desired territory expansion, employees, and years of franchising experience as the inputs. This is as close as my data will allow me to get to their specification. They use sales as the output, and cost (measured by multiplying the hotel's star rating by a fixed amount), territory coverage, and chain duration as their inputs. After I calculate efficiency scores, I test for differences across groups of chains grouped by ownership mix.

I then extend the work of Botti et al. by attempting to explain the factors that influence the efficiency score. To do this, I estimate the following equation:

$$\begin{aligned}\Theta_{t-1} = \alpha_0 + \alpha_1(\%\mathit{franchisee})_{t-1} + \alpha_2(\mathit{outlets})_{t-1} + \alpha_3(\mathit{years\ franchising})_{t-1} \\ + \alpha_4(\mathit{royalty})_{t-1} + \alpha_5\big((\mathit{royalty})_{t-1} \times (\%\mathit{franchisee})_{t-1}\big) + \gamma \quad (4.1)\end{aligned}$$

where Θ_{t-1} is the DEA efficiency score in year $t-1$ and γ is a vector of sector dummy variables. If α_1 is positive, that would signify that a higher percentage of franchisee-ownership results in a higher efficiency score. This is an indication that the agency theory is correct. A larger percentage of franchisee ownership means that more establishments are managed by someone with a ownership-stake. This results in higher efficiency for the chain as a whole. If α_1 is negative, that means that higher franchisee-ownership results in lower efficiency scores.

The number of outlets from year $t-1$ is included to control for the size of the chain. Economies of scale can help a chain be more efficient, so I expect α_2 to be positive. The same should be true for years of experience. The royalty rate from year $t-1$ is included to control for the level of interest the franchisor has in the franchisees' success. The higher the royalty, the more invested the franchisor is because they get more revenue from the success. Therefore, α_4 should be positive. The interaction term is there to discount the effect of the royalty as the percentage of franchisee ownership changes.

I further extend the franchising literature by using the estimated efficiency score to predict how the ownership mix changes in the next year. I estimate the following equation:

$$\Phi_t = \beta_0 + \beta_1\hat{\Theta}_{t-1} + \beta_2(\textit{years franchising})_{t-1} + \beta_3(\textit{years franchising})^2_{t-1} \\ + \beta_4(\textit{outlets})_t + \beta_5(\textit{outlets})^2_t + \beta_6(\textit{royalty})_t + \beta_7(\textit{recession})_t + \beta_8(\textit{post recession})_t + \gamma \quad (4.2)$$

where $\hat{\Theta}_{t-1}$ is the fitted efficiency score from equation (4.1), Φ_t is the percentage-point $\textit{recession}_t$ is a dummy variable indicating if the economy is in a recession in year t, and $(\textit{post recession})_t$ is a dummy variable indicating if the economy is in a post-recession recovery in year t. The recession dummies are important because they control for economic conditions that franchisors face, especially with respect to available capital.

The next logical question to ask is whether the chain's efficiency affects the franchise fee that the firm charges. I estimate the following equations:

$$\textit{fee} = \delta_0 + \delta_1\Theta_{t-1} + \delta_2(\textit{outlets})_t + \delta_3(\textit{outlets})^2_t + \delta_4(\textit{years franchising})_t + \\ \delta_5(\textit{years franchising})^2_t + \delta_6(\textit{financing available})_t + \gamma \quad (4.3)$$

and

$$\textit{fee} = \zeta_0 + \zeta_1(\textit{rank}_t) + \zeta_2(\textit{outlets})_t + \zeta_3(\textit{outlets})^2_t + \zeta_4(\textit{years franchising})_t + \\ \zeta_5(\textit{years franchising})^2_t + \zeta_6(\textit{financing available})_t + \gamma \quad (4.4)$$

where *rank* is the *Franchise 500* ranking and (*financing available*) is a dummy variable that equals one if the franchisor facilitates financing for potential franchisees. *fee* is adjusted for all years into 2013 dollars. Both the rank and the efficiency score are an indication of the quality of the chain. If rank if high (closer to one), then that is a signal to potential franchisees that that chain is a good one to be a part of. It is also a somewhat weak proxy for the brand value of the chain. The *Franchise 500* says that the size of the chain, the growth rate, and financial stability of the chain are all taken into account when calculating the ranking. The same story is true for the efficiency score, Θ. A higher efficiency score indicates that the chain is better operated, which makes it more desirable to be a franchisee. If δ_1 and/or ζ_1 are positive, that indicates that better-operated chains charge higher franchise fees. If they are negative, that indicates that better-operated chains charge lower franchise fees. If the theory that franchise fees are simply used to recoup startup costs is true, then the sign on rank and the efficiency score should be zero or negative. In other words, better run chains should have lower start up costs than worse run chains, or at least have the same costs.

4.2.1 Replication of Lafontaine and Shaw (1999)

The data that I have allow for one more important contribution to the literature. Lafontaine and Shaw (1999) is one of the most influential papers in the franchising literature. However, their data are thirty years old, and are mostly from a world without significant technological implementation (the latest year is 1992, which is before the internet became commonplace). The data that I have are from the same source they used in their analysis, but are much newer. This allows me to replicate three of their key findings.

First, I look at how the franchise fee and royalty are determined. Then I look at how the franchise fee relates to the royalty rate. They find that chain size has a positive effect on both the rate and the fee, but that both effects are smaller after controlling for firm fixed effects. They also find that there is a negative relationship between the franchise fee and the royalty rate. However, as I will discuss below, they change their conclusion after taking out ongoing fixed royalties (which they lump into the fee). The replication is an important part of this paper because it checks whether a key paper in the literature is still valid, and it also serves as a check to my data, which supports the analysis described above.

4.3 Data

I draw my data from two sources: the *Franchise 500* and Business Insights. The first set of data come from published editions of the *Franchise 500* dating from 2004 to 2012, inclusive. The *Franchise 500* is a list of the top 500 franchised chains, published yearly in the January issue of *Entrepreneur Magazine*. As a result, the previous year's information is presented, so 2012's data is in the January 2013 edition. Firm are required to submit contract information in order to be included in the sample. The publisher then checks the data and ranks the franchisors. There is not a clear ranking formula published. However, the *Franchise 500* is designed to help entrepreneurs make an informed decision when considering becoming a franchisee. According to the 2016 *Franchise 500* summary of the ranking process, *Entrepreneur Magazine* takes into account the franchisor's financial strength and stability, the growth rate, and the size of the chain. Chains that are not taking new franchisees, or are in bankruptcy, are not eligible to be ranked. In order to be considered, franchisors need to submit franchise disclosure documents to the publishers, who independently review the information the franchisor provided.

Table 4.1: The number of establishments included in each years' *Franchise 500*.

Year	Chains
2004	743
2005	783
2006	760
2007	817
2008	807
2009	738
2010	758
2011	777
2012	824
Total	7007

Each year the *Franchise 500* ranks the top 500 franchise systems, but additional chains are also listed. This provides data for more than 500 chain each year in the sample. The year with the fewest data points is 2009 with 738 chains, and 2012 has the most with 824. Chain counts for all nine years are presented in Table 4.1. This is an unbalanced sample, at least partially caused by companies not submitting data each year. There does not seem to be any systematic inclusion or exclusion in the data. There are 230 chains that appear in the data across all nine years. There is some concern about bias here due to chains' choice regarding submitting data to the *Franchise 500*. As Lafontaine and Shaw (1999) discuss, chains submitting data are likely trying to woo potential franchisees through being included in the list. That means that chains that are not looking to expand are likely not going to go to the trouble of being included. This has the potential to bias the sample toward franchisors that are growing aggressively.

The data collected and presented by the *Franchise 500* is quite extensive. For each chain for each year the number of company-owned and franchisee-owned stores is presented for the current and previous two years. This makes it easier to check for store count data entry errors. Additionally, startup costs, royalty rates, and franchise fees are listed for each chain along with the year the company was founded and the year the company started franchising. Finally, the geographic areas of expansion and details on financing, home-based opportunities, and kiosks are given.

Table 4.2 presents summary statistics on each of the key contract terms as well as the number of company and franchisee outlets. Summary statistics from Lafontaine and Shaw (1999) are also listed to provide a comparison. There is not a constant number of observations because not all data points appear for each chain. Both a lack of reporting and low-quality scanned versions of the *Franchise 500* contributed to this. Another factor contributing to the unbalanced nature of the variables is how contract terms are structured. The vast majority of chains use a percentage of sales to calculate the royalty. There are some chains, however, that use other methods, such as a per-unit or per-month amount. These chains are not included in the average royalty data because there is no way to standardize it with the rest of the sample.[10] On average, chains have many more franchisee-owned stores than company-owned stores. The average chain owns 52 stores themselves and franchises 537 stores. The largest chains in the sample are McDonald's, 7-Eleven, and Subway.

The means for all of the contract terms are statistically different from the values in Lafontaine and Shaw (1999). This is not surprising, and is not cause for concern. The time difference between their data and mine will naturally lead to differences in contract terms, on average, as new firms enter and other firms exit the market. The data from Lafontaine and Shaw are in 1992 dollars. I

[10]Lafontaine and Shaw include these as discounted values for the fee. However, they point to some key problems that this poses for their analysis, so I ignore them.

have adjusted the franchise fee and capital requirements to be in 2013 dollars across all years. Their mean fee of $23,300 is $38,687.80 in 2013 dollars, and their mean capital requirement of $174,800 is $290,241.51 in 2013 dollars. There is a large difference in the average capital requirement in my data from theirs. They do not state how their capital requirement is defined. In the *Franchise 500* during my sample, a high and low value were provided, and I am presenting the average of those high and low values.

Table 4.2: Summary statistics for contract terms in the *Franchise 500* and the years of franchising experience. These numbers are compared with results from Lafontaine and Shaw (1999).

	Present Paper			Lafontaine and Shaw (1999)		
Variable	Observations	Mean	St. Dev.	Observations	Mean	St. Dev.
Royalty	5,110	5.8	3.1	11,947	6.4	3.5
Fee (1,000's)	5,074	31.5	15.7	11,947	23.3	36.8
Capital Required (1,000's)	6,918	635.6	3,416.7	11,744	174.8	686.7
Years Franchising	7,007	15.7	12.8	11,947	9.4	9

I provide a summary of contract terms by sector in Table 4.3. There is a wide variation in the number of units across sectors. The quick service food sector is by far the largest. There is very little variation in royalty rates or franchise fee across sectors. The number, and therefore, the percentage of units owned by the franchisor (comp. units) also varies a lot by sector. Just under three quarters of units are franchisee-owned in the financial services sector, whereas 99% of units are franchisee-owned in the maintenance sector.

The second source of data is Business Insights, an online database of financial data. Business Insights provides data for both publicly-traded and private companies (including subsidiaries). This is more thorough than can be found in other databases that only included public companies. The trade-off is that a much smaller subsample is included in the Business Insights data than is in the Franchise 500 data. There are 87 chains that have data in both the *Franchise 500* and Business Insights for the relevant years. More chains can be found in Business Insights, but not for the years covered by the *Franchise 500*. The Business Insights data provides information on the revenue generated by the company and the number of people employed by the firm. These are company-level data. In franchise systems, that likely means that employees at franchisee-owned establishments are excluded from the total. As for revenue, since the franchisor receives a percentage of revenue from

Table 4.3: Summary of contract terms by sector.

Sector	Firms	Mean Royalty	Royalty St. Dev.	Med. Royalty	Mean Fee	Fee St. Dev.	Med. Fee	Mean Fran. Units	Mean Comp. Units
Automotive	236	6.11	3.54	6	29039.06	16755.8	27500	374.47	17.98
Business Services	323	7.05	5.83	6	32056.48	16244.08	29500	188.75	9.30
Children's Businesses	395	6.55	3.2	7	32893	22079.09	29900	501.4	13.37
Children's Products & Services	35	6.31	3.05	6	27006.98	15796.77	27500	647.92	16.13
Financial Services	117	10.31	7.46	10	30521.25	23937.46	29700	466.69	188.92
Food/Full-Service Restaurants	212	4.55	0.71	4.75	36205.45	8769.92	35000	152.01	48.24
Food/Quick Service	1261	5.22	1.39	5	26783.87	8248.2	25000	892.91	121.46
Food/Retail Sales	135	4.64	1.84	5	28697.56	7079.69	30000	129.95	11.40
Health	52	6.03	2.58	6	33550	12356.84	30000	190.64	45.55
Health Businesses	8	6.63	2.45	6.5	24423.08	10465.91	25000	266.53	238.29
Home Improvements	270	5.14	1.9	5	32239.46	17045.96	29900	152.92	3.08
Hotels & Motels	158	4.66	0.7	5	47920.72	22683.28	45000	772.43	55.28
Maintenance	410	6.89	2.4	6	25060.72	14573.54	24500	591.73	6.67
Personal Care	429	5.59	2.31	6	29386.16	11076.46	29000	459.74	34.46
Pets	82	5.57	1.54	5	26696.97	12241.16	29500	106.57	2.90
Recreation	107	5.79	3.9	5	21287.06	14668.73	25000	244.42	5.25
Retail	265	4.54	1.97	5	26000.4	11648.82	25000	1507.05	224.37
Services	550	6.18	3.61	6	27881.32	10892.07	26900	397.68	9.72
Tech	64	8.33	3.1	8	27608.06	11356.8	25000	278.56	4.08

the franchisee in the form of royalty payments, the franchisor's revenue will reflect the success of the franchisees. It is possible that there is additional revenue coming from other sources as well. It is impossible to distinguish where the revenue is coming from with the data here.

4.4 Results

Botti et al. (2009) find that franchise chains with an ownership mix between franchisees and franchisors are more efficient than chains that are only franchisee-owned or are almost entirely franchisor owned. However, they do not find statistical significance in their data. After calculating DEA scores for each establishment for each year in my sample, I break them up into five categories: less than 25% franchised, between 25% and 74% franchised, between 75% and 89% franchised, between 90% and 99% franchised, and 100% franchisee-owned. The results, with means for the full sample and the hotel-only sample are in Table 4.4. Casual observation shows that the mean efficiency score is highest for mixed ownership for both groups. That plays out for the full sample with a difference in means test. For the full sample, the F-statistic for the difference in means by ownership group is 4.42, which is significant at the 1% level (p-value = 0.002). The same is not true for the hotels. For hotels, the F-statistic is 2.1, which is not significant at any level (p-value = 0.14). This result is not dissimilar to Botti et al. The most likely problem, like in their paper, is that the sample of hotels is small.

In addition to the groupings of ownership percentage, Table 4.5 provides a list of all of the sectors, the number of observations, the mean efficiency score, and the average percentage of franchisee-ownership. Again, casual observation shows that sectors that have high, but not exclusive, franchisee-ownership (so, therefore, have some mix) have the highest average efficiency score.

Table 4.4: Mean DEA efficiency score by the percentage of the chain that is franchisee owned. Results for both the full sample and the hotel sample are presented.

	Full Sample		Hotels	
Ownership Group	Observations	Mean Efficiency	Observations	Mean Efficiency
Less than 25%	2	0.257	0	–
Between 25% and 74%	30	0.323	5	0.577
Between 75% and 89%	17	0.395	4	0.134
Between 90% and 99%	91	0.228	5	0.523
100%	73	0.153	7	0.478

Table 4.5: Mean DEA efficiency score by sector for chains found in the *Franchise 500* and Business Insights. The efficiency scores were calculated using revenue as the output and employment, franchising experience, and territory coverage as the inputs.

Sector	Observations	Mean Efficiency Score	% Franchisee-Owned
Automative	8	0.139	98.55
Business Services	4	0.344	81.39
Children's Businesses	2	0.053	100
Financial Services	7	0.233	64.6
Food/Full Service	5	0.049	93.24
Food/Quick Service	73	0.268	91.45
Food/Retail Sales	12	0.154	98.07
Health Businesses	1	0.258	43.3
Home Improvement	2	0.308	99.81
Hotels & Motels	21	0.367	85.82
Maintenance	24	0.139	99.61
Personal Care	13	0.128	84.17
Pets	9	0.129	98.43
Retail	17	0.428	82.51
Services	12	0.077	95.37
Tech	3	0.008	100

If the results from Essay II, paired with the results in the replication of Botti et al., suggest that franchisee-ownership matters, then what determines changes to the percentage of ownership within firms? As described above, I approach that question with a two-stage least squares model. In the first stage, I estimate equation (4.1). Those results are in Table 4.6. While not significant, the coefficient on the percentage of establishment owned by franchisees is positive. A positive sign signifies that higher franchisee-ownership translates into higher efficiency. Since the coefficient is insignificant, it is hard to draw hard conclusions, but the coefficient is positive and significant when the current year is used instead of the lagged year (0.90 with a p-value of 0.04). The analysis here needs the lagged value because it will be plugged into equation (4.2). However the positive and significant coefficient on the present-year percentage franchisee ownership variable indicates that the results from Botti et al. translate into two-stage DEA, and that they still hold when other variables are included. This suggests that increasing franchisee ownership can lead to higher efficiency, holding other factors constant.

Additionally, the positive sign on the outlets coefficient suggests that larger chains will be more efficient. Due to potential economies of scale, this is not surprising. The negative sign on the years of experience variable, however, is interesting. This is suggesting that more experienced chains will

Table 4.6: First stage regression relating the percent of establishments owned by franchisees to the efficiency score, all lagged one year.

Variable	Coefficient
(% Franchisee)$_{t-1}$	0.82
	(0.58)
(Outlets)$_{t-1}$	0.0029***
	(0.00004)
(Years Franchising)$_{t-1}$	-0.70***
	(.19)
(Royalty)$_{t-1}$	15.69**
	(8.21)
(Royalty)$_{t-1}\times$(% Franchisee)$_{t-1}$	-0.22**
	(0.10)
Constant	2.14
	(47.54)
Sector Dummies	Y
Observations	80

be less efficient. Finally, the royalty rate is positive, but that reduces as the percentage of franchisees increases. Higher efficiency resulting from higher royalty rates makes sense in with respect to the agency theory. The more revenue that the franchisor gets from the establishments, the more they will care about their profitability. This gives the franchisor a stronger incentive to innovate and advertise.

Equation (4.1) generates fitted values, $\hat{\Theta}_{t-1}$, which are then plugged into equation (4.2). The results from equation (4.2) are in Table 4.7. The coefficient on the fitted efficiency score is negative and insignificant. Again, it is hard to draw conclusions based on an insignificant result. At most, it can be said that past performance, in this sample, does not seem to have much, if any, effect on ownership mix changes.

More years of franchising experience will result in smaller changes in franchisee-ownership at an increasing rate. This fits with the results from Lafontaine and Shaw (2005). Figure 4.1 uses my data to show that average percentage of company-owned stores falls for about the first seven years, and then levels off. This graph looks almost identical to one published by Lafontaine and Shaw. If chains find their mix of ownership early in their life cycle, more years of experience will lead to less change in ownership mix.

Additionally, as the number of outlets grows, the change in franchisee ownership decreases.

Table 4.7: Second stage regression results. The dependent variable is the percentage point change of franchisee-ownership.

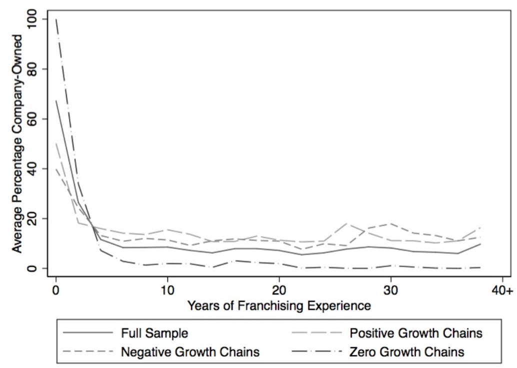
Variable	Coefficient
$\hat{\Theta}_{t-1}$	-0.03
	(0.02)
(Years Franchising)$_t$	-0.08*
	(0.003)
(Years Franchising)$_t^2$	0.003**
	(0.001)
Outlets$_t$	-0.001***
	(0.0002)
Outlets$_t^2$	0.000002***
	(0.00)
Royalty$_t$	0.15***
	(0.06)
(Recession Dummy)$_t$	0.31
	(0.5)
(Post Recession Dummy)$_t$	-0.57
	(0.58)
Sector Dummies	Y
Observations	77

This also makes sense. As franchisors gain experience, they make fewer changes to their ownership structure.

Just to be clear, neither of these results are suggesting that the *number* of franchisee-owned stores is not changing. They are simply suggesting that the percentage of franchisee-owned stores is not growing as much. There seems to be ample evidence that the experience franchisors gain, both through stores and years, leads to a steady mix and fewer changes. Then it makes sense that short-term efficiency scores probably don't have much effect on ownership mix changes. If franchisors have found a mix that works for them, it is best to only change that in dire circumstances. Having a lower efficiency score relative to other firms may not fit that criteria.

Next, I move to an attempt to explain the franchise fee. The results from equations (4.3) and (4.4) are in Table 4.8. Both rank and the efficiency score have the expected sign, although only the efficiency score is significant. The negative sign on rank says that higher ranked chains (that is, closer to one) charge higher fees. The coefficient on the efficiency score says that more efficient chains are able to charge higher fees. The positive relationship between quality and fee harkens back to some of the franchising theory (see: Mathewson and Winter (1985)), but it does not fit with

Figure 4.1: Percentage of outlets owned by the franchisor by years of franchising experience. The full sample, plus subsamples based on the direction of growth are presented.



Lafontaine and Shaw (1999). They find that chains do not use the fee as a way to collect rents, but instead use it to recoup expenses. This suggests otherwise. Better managed chains get a higher efficiency score, and are also more attractive to franchisees. In a market for franchisees, this allows the franchisor to charge a higher price.

The two experience variables, years franchising and outlets, move in opposite directions and are both significant. The fee falls with the size of the chain, but falls at a decreasing rate. Additionally, the fee rises with years of experience, but at a decreasing rate. I also run this regression with neither rank nor outlets, to match what Lafontaine and Shaw run, and those results are in Table 4.9. The results in Table 4.8 are very similar to the results in Table 4.9. Despite the difference in the sample size, the signs are the same and the magnitudes are larger. I do not run the firm fixed effects model on the smaller sample because there is not enough variation within firms. For the regressions with sector dummies, in sections (1) and (2) in Table 4.9, my signs are opposite of theirs. This is likely due to our different definitions for the franchise fee. They include any on-going fixed royalty rates (e.g., a royalty of $50 per month) as part of the fee. However, in their discussion they backtrack and suggest that their results change when these royalties are not included in the fee. I ignore these flat royalties, and include them in neither the royalty nor the fee. These chains represent a small percentage of the overall sample.

In the interest of completeness, I also replicate Lafontaine and Shaw (1999) in two other ways. First, I look at the determinants of the royalty, similarly to the results discussed above. Those

Table 4.8: Regressions relating franchise fee to chain characteristics. The dependent variable is the franchise fee in time t. The fee has been divided by 1000 and adjusted for inflation into 2013 dollars.

	(1)	(2)
Rank_t	-0.005	
	(0.01)	
Θ_{t-1}		0.11*
		(0.06)
Outlets_t	-0.37***	-0.40***
	(0.00)	(0.11)
Outlets_t^2	0.00001***	0.00001***
	(0.00)	(0.00)
$(\text{Years Franchising})_t$	0.65**	0.50
	(0.31)	(0.31)
$(\text{Years Franchising})_t^2$	-0.007	-0.006
	(0.005)	(0.004)
Financing_t	-2.39	-3.03
	(2.39)	(2.43)
Constant	34.69***	37.87***
	(7.98)	(7.32)
Sector Dummies	Y	Y
N	76	77

results are in Table 4.10. Here I am able to generate similar results to Lafontaine and Shaw. I get more significance in the firm fixed effects versions (sections (1) and (2)), but signs are the same, and magnitudes are not too far off for many of the estimated coefficients. This suggests that chains follow much the same royalty setting procedures as they did thirty years ago.

It makes sense that royalty-setting patters are similar to historical patters given the fact that franchisors rarely change their royalties. This can be seen in Table 4.11 and Figure 4.2. It is still true that franchisors are more likely to change their fee than their royalty. Considering Lafontaine and Shaw's theory that the fee is more to recoup the franchisors expenses in setting up a new franchisee than to capture rents, it is not surprising that this pattern holds over time. As the franchisor's expenses change, they change their fee accordingly. The royalty rate stays more consistent, reflecting its position as a revenue generator. A similar pattern can be found in Figure 4.2. The probability of a franchisor changing their royalty rate is much lower than changing their franchise fee. Like Lafontaine and Shaw found, there is little evidence of any relationship between years of experience and changing of contract terms.

I conclude by looking at the relationship between the franchise fee and the royalty. The results

Table 4.9: OLS and fixed effects examining determinants of the franchise fee, which is the dependent variable. Standard errors are listed in parentheses. ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level.

	(1)		(2)		(3)		(4)	
	Sveum	LS	Sveum	LS	Sveum	LS	Sveum	LS
Outlets	-0.13***	0.435***	-0.12***	0.338***	0.56***	-0.009	0.55***	0.032
	(0.03)	(0.116)	(0.03)	(0.120)	(0.1)	(0.261)	(0.09)	(0.262)
Outlets^2	0.000004***	-0.007***	0.000004***	-0.006***	-0.00001***	-0.002	-0.00001***	-0.003
	(0.092)	(0.002)	(0.000001)	(0.002)	(0.000002)	(0.004)	(0.000002)	(0.004)
Years Franchising	0.22***	0.045	0.19***	0.042	-0.08	-0.292	-0.08	-0.259
	(0.045)	(0.068)	(0.04)	(0.067)	(0.11)	(0.729)	(0.11)	(0.733)
(Years Franchising)^2	-0.002***	-0.003***	-0.003***	-0.003***	-0.004**	-0.001	-0.003	-0.005
	(0.0009)	(0.001)	(0.0009)	(0.001)	(1.39)	(0.004)	(0.001)	(0.004)
Financing Provided			2.22***	2.130			0.87***	-1.640***
			(0.47)	(.838)			(0.28)	(0.623)
Capital Requirement			0.001***	0.003***			-0.0001	0.1
			(0.00007)	(0.001)			(0.00009)	(0.4)
Constant	27.67	25.860***	26.44***	24.91***	25.5***		24.43	
	(1.29)	(1.310)	(1.32)	(1.33)	(5.37)		(5.3)	
Sector Dummies	Y		Y		N		N	
Firm Fixed Effects	N		N		Y		Y	
Year Dummies	Y		Y		Y		Y	
Observations	5074	11947	5003	11728	5074	11947	5003	11728
R^2	0.09	0.051	0.13	0.051	0.88	0.046	0.88	0.040

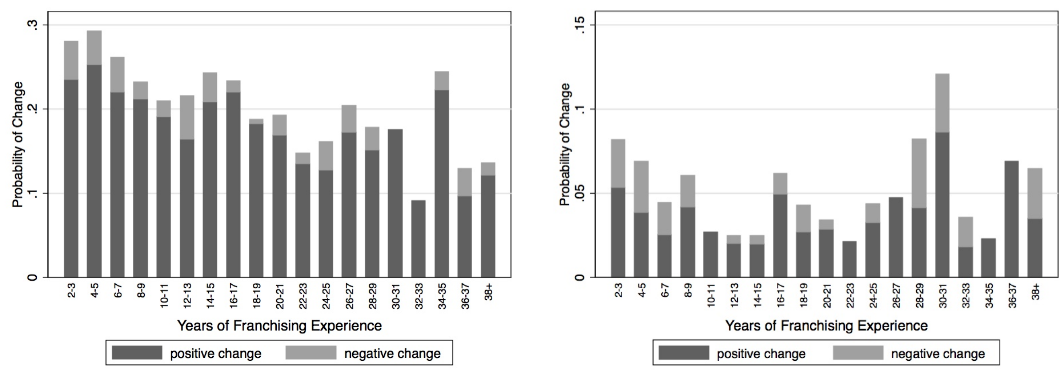
Table 4.10: OLS and fixed effects examining determinants of the royalty rate, which is the dependent variable. Standard errors are listed in parentheses. ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level.

	(1)		(2)		(3)		(4)	
	Sveum	LS	Sveum	LS	Sveum	LS	Sveum	LS
Outlets	.024***	0.103***	.024***	0.103***	.039***	0.033	0.04***	0.035*
	(.005)	(0.16)	(.005)	(0.016)	(.008)	(0.02)	(0.008)	(0.021)
Outlets^2	-0.00005***	-0.001***	-.0000005***	-0.001***	-0.0001***	-0.0006*	-0.00001***	0-0.001
	(.00002)	(0.0003)	(.0000002)	(0.0003)	(0.00002)	(0.0003)	(0.000002)	(0.0006)
Years Franchising	-0.03	-0.001	-.0081	-0.003	0.05***	-0.085	0.05***	-0.178**
	(.009)	(0.009)	(.009)	(0.009)	(.022)	(0.060)	(0.021)	(0.071)
(Years Franchising)^2	.0001	-0.0005***	0.00008	-0.004***	-0.0012***	0.002***	-0.001***	0.001
	(.0002)	(0.0002)	(.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0006)
Financing Provided			-.25***	0.452***			-.132***	-0.066
			(.095)	(0.086)			(0.048)	(0.077)
Capital Requirement			-0.00001	0.00				
			(0.00001)	(0)				
Constant	5.94***		6.08***		10.52***		10.63***	
	(.25)		(.26)		(.89)		(.89)	
Sector Dummies	Y		Y		N		N	
Firm Fixed Effects	N		N		Y		Y	
Year Dummies	Y		Y		Y		Y	
Observations	5110	11947	5051	11728	5110	11947	5110	11728
R^2	0.12	0.072	0.12	0.074	0.92	0.022	0.92	0.023

Table 4.11: Number of changes to key contract terms per chain.

	Total Sample		Balanced Sample	
Number of Changes	Royalty	Fee	Royalty	Fee
0	1692	1398	191	102
1	119	280	31	59
2	18	95	6	37
3	4	34	2	15
4	0	16	0	8
5	0	6	0	5
6	0	2	0	2
7	0	1	0	1
8	1	1	0	1

Figure 4.2: Probability of positive or negative changes in contract terms, by years of franchising experience.



(a) Franchise Fee

(b) Royalty Rate

are in Table 4.13. Sections (1) and (2) use the royalty rate as the dependent variable, whereas sections (3) and (4) use the franchise fee as the dependent variable. Section (1) and (3) do not use firm fixed effects, and Sections (2) and (4) do. Within each section, three columns are presented. The first columns are my results using OLS. The second columns are my results using a simultaneous estimation process where the fee and royalty are jointly determined. The third columns are Lafontaine and Shaw's OLS results. They also present instrumented results, but I leave those out for space reasons. I find that there is a positive relationship between the franchise fee and the royalty rate in both directions. This is the opposite of what Lafontaine and Shaw find. They find a negative relationship between the franchise fee and royalty. I also examined these specifications using just the firms that appear in all years, but found similar results. That table is not shown.

There is a clear concern that the royalty rate and the franchise fee are simultaneously determined.

Table 4.12: Regressions relating the franchisee fee to the royalty rate with the royalty as the dependent variable. Standard errors are listed in parentheses. ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level.

	(1)			(2)		
	OLS	3SLS	LS	OLS	3SLS	LS
Outlets	0.016***		0.093***	0.05***		0.33
	(0.006)		(0.15)	(0.016)		(0.020)
Outlets^2	-0.00003*		-0.001***	-0.0001***		-0.001*
	(0.00002)		(0.00)	(0.00003)		(0.00)
Years Franchising	-0.034***		0.006	0.053***		-0.086
	(0.0103)		(0.008)	(0.013)		(0.060)
(Years Franchising)^2	0.0006***		-0.001***	-0.001***		0.002***
	(0.0002)		(0.00)	(0.0003)		(0.000)
Franchise Fee	0.013***	-0.165***	-0.010***	0.014***	0.02***	-0.014***
	(0.003)	(0.02)	(0.001)	(0.003)	(0.003)	(0.001)
Royalty Rate						
Constant	5.37***	11.12***	6.78	10.1***	5.03***	
	(0.2)	(0.63)	(0.143)	(0.84)	(0.12)	
Firm Fixed Effects	N	N	N	Y	Y	Y
Observations	3869	3869	11947	3869	3869	11947
Adj. R^2	.008		0.025	0.92		0.051

Table 4.13: Regressions relating the franchisee fee to the royalty rate with the fee as the dependent variable. Standard errors are listed in parentheses. ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level.

	(3)			(4)		
	OLS	3SLS	LS	OLS	3SLS	LS
Outlets	-0.12***		0.478***	0.46***		0.066
	(0.03)		(0.108)	(0.1)		(0.246)
Outlets^2	0.000004***		-0.008***	-0.000007***		-0.003
	(0.000001)		(0.002)	(0.000002)		(0.004)
Years Franchising	0.25***		0.045	0.09		-0.474
	(0.05)		(0.072)	(0.14)		(0.721)
(Years Franchising)^2	-0.003***		-0.004***	-0.004**		0.003
	(0.001)		(0.001)	(0.001)		(0.004)
Franchise Fee						
Royalty Rate	0.33***	-5.51***	-1.12***	0.56***	0.57***	-2.25***
	(0.08)	(0.71)	(0.132)	(0.12)	(0.08)	(0.118)
Constant	27.91	65.47***	33.99***	19.4***	29.27***	
	(0.99)	(4.12)	(2.19)	(5.5)	(0.53)	
Firm Fixed Effects	N	N	N	Y	Y	Y
Observations	3869	3869	11947	3869	3869	11947
Adj. R^2	.014		0.021	0.88		0.074

Lafontaine and Shaw attempt to get around this by instrumenting the contract terms using lagged variables. They end up rejecting their instrument as not good enough. To get around this problem, I estimate the royalty and fee jointly using three stage least squares. I find that, with sector dummies, I get a negative relationship between the fee and the royalty, in both directions. This is similar to what Lafontaine and Shaw find, and fits more closely with the theory. When I substitute firm fixed effects, the signs switch positive, like my OLS results.

Lafontaine and Shaw end up rejecting their negative coefficients. Despite the fact that they get negative and significant results, they turn their attention back to the way that they constructed the franchise fee. For firms that charge an on-going dollar amount instead of a traditional percentage royalty, they discount that amount and add it to the up-front free. Once they remove those firms from the analysis, the sign on the outlet size coefficient goes positive. They do not provide a table with these coefficients, so I can not compare them to my findings, but I do find positive coefficients. This suggests that the positive relationship between the number of outlets and the franchise fee is correct. This is further conformation of their theory that the fee is designed to recoup start up costs, so it should not change with chain size.

4.5 Conclusion

In this paper I combine the literature that examines how efficiency and ownership mix are related with the literature that examines how ownership mix is determined. I find that ownership mix does have a positive effect on efficiency, although it does not keep its significance when put in a regression with other factors. I then conclude that efficiency has a very small, negative, and insignificant effect on ownership mix change decisions. I also find that efficiency has a positive and significant effect on the franchise fee. This is in contrast with previous literature that shows that the fee does not vary with chain quality, but is instead designed to recoup startup costs. My results suggest that more efficient, and therefore better run chains, can increase their fee because they are providing more value to their franchisees.

I also look at some of the key results from Lafontaine and Shaw (1999), and find that some of their results hold up better than others. I am able to successfully replicate their results on the determinants of the royalty. I get opposite signs, and more significance, than they do on determinants of the fee. And I get opposite signs from them on the relationship between the fee and the royalty. However, some of these results are based on the difference in our definition of the fee. Once they change their definition of the fee, our results are similar. So another contribution of this paper is that it presents a full table on the relationship between the fee and the royalty, whereas Lafontaine and Shaw present these corrected results as a brief discussion.

This work is an important contribution to the franchising literature because of the way that it ties these two areas of the literature together. It explains more about how ownership change decisions are made, and it explain how franchisors behave using more updated data. Future research can make this stronger by assembling an even more comprehensive set of financial data to pair with the *Franchise 500* data. This will make for even stronger conclusions.

5 Summary and Future Research

These three essays, taken together, provide a fuller picture of the relationship between the frequently-observed organization form of franchising, and the productivity of establishments and chains. The findings in the three essays give insights into the decisions that franchisors make, and the results of those decisions.

Essay I provides evidence that data envelopment analysis is a worthy tool for determining the effects that the franchising decision has on productivity. After simulating restaurants using a production function based on real world data, I add a boost to output for establishments that are randomly assigned franchisee ownership. As I vary the amount of the bonus (between five and 50 percent), the difference in output grows. I then find that the second stage of the two-stage DEA process is able to pick up on these output differences. The estimated coefficients of the difference between franchisee- and franchisor-owned establishments is less than the franchisee bonus, but that is to be expected, as explained in Essay I. The main conclusion is that two-stage DEA is able to pick up on a known differences between two groups. The context of the essay is franchising, but the application is much wider reaching. Any researcher can use two-stage DEA in cases where the objective is to compare two groups. This is especially valuable in cases such as Essay II, where there is good reason to use multiple outputs, leaving more traditional measures of productivity less applicable.

Essay II applies the procedure from Essay I to non-public use data from the United States Census Bureau's Census of Retail Trade. I narrow the focus to franchisee- and franchisor-owned establishments in the full service and limited service restaurant subsectors. I conduct two different DEA scores for each restaurant. The first uses total sales as the output, and the second uses a combination of categories of sales (drive thru, counter, and takeout for limited service, and server and takeout for full service). Both measures of DEA use payroll, seats, and the age of the establishment as the inputs. I find a statistically significant positive franchisee-ownership effect for both measures of DEA in the full service subsector, but not in the limited service subsector. I suggest that this is due to the nature of managerial decisions and actions within each type of establishment. Full service restaurants provide much more of an opportunity for managers to train employees and impact the service provided. This essay makes an important contribution to the franchising literature because it shows that, at least for full service restaurants, ownership matters. This serves a confirmation that the agency theory of franchising is correct.

Essay III uses *Franchise 500* data to examine how changes to the ownership mix are determined. I hypothesize that franchisors look to past efficiency as a guide for making changes in ownership. I find that there is no evidence that past inefficiencies lead to more or less franchisee growth. This fits with past literature, though, in that it suggests that franchisors target a specific ownership mix, and then expand accordingly, but do not deviate from that mix. Therefore, one year of inefficiency compared with other firms will not make franchisors change ownership mix. This is an important contribution to the franchising literature because it ties together the literature that examines that determinants of ownership mix and the literature that examines how chain efficiency changes across groups of ownership mix. I also contribute to the literature by reexamining Lafontaine and Shaw (1999), a widely cited paper that uses old data. I find that many of their results are still valid today, but find a couple of notable exceptions.

My future research agenda will be heavily focused on the extensions of Essay II. The analysis in Essay II is a cross-sectional look at restaurant productivity. In the proposal process Dr. Sykuta and I have been given access to data from 2002, 2007, and 2012. The next step is to add in the 2002 and 2012 data to see what changes over time can be detected. Particularly, changes in ownership can lead to interesting conclusions on the change in productivity. Additionally, I have the data to compare franchisee-owned establishments to independently-owned establishments. This will allow me to examine the effect of the franchise relationship that franchisees get but independent owners do not. Finally under the current Census approved project, I want to draw in contract terms. One of the motivating factors for digitizing the *Franchise 500* was to be able to apply those contract terms to the Census data.

Outside of the current approved Census project, I plan to write a new proposal to look at the decision to franchise. The current project looks the the effects of that decision, but I think that the better question might have been “how do franchise chains determine whether they own a store of whether they franchise it?”

Combined with the present research, this future research agenda has the potential to significantly advance the franchising literature. Essay II and its extensions use a dataset that very few other people have access to, and I am not aware of any active researchers using the franchise question in the Census of Retail Trade. This data is a very rich data source, and having access to it gives me an opportunity to contribute to the understanding of franchising as an organizational form.

References

Achabal, Dale D, John M Heineke, and Shelby H McIntyre, "Issues and Perspectives on Retail Productivity," *Journal of Retailing*, October 1984, *60* (3), 1–23.

Affuso, Luisa, "An Empirical Study on Contractual Heterogeneity Within the Firm: The 'Vertical Integration-Franchise Contracts' Mix," *Applied Economics*, 2002, *34*, 1–16.

Anderson, Randy I, Robert Fok, Leonard V Zumpano, and Harold W Elder, "The Efficiency of Franchising in the Residential Real Estate Brokerage Market," *Journal of Consumer Marketing*, 1998, *15* (4), 386–396.

Betancourt, Roger R, *The Economics of Retailing and Distribution*, Cheltenham: Edward Elgar Publishing Limited, 2004.

Bhattacharyya, Sugato and Francine Lafontaine, "Double-Sided Moral Hazard and the Nature of Share Contracts," *The RAND Journal of Economics*, 1995, pp. 761–781.

Botti, Laurent, Walter Briec, and Gérard Cliquet, "Plural Forms Versus Franchise and Company-Owned Systems: A DEA Approach of Hotel Chain Performance," *Omega*, June 2009, *37* (3), 566–578.

Brickley, James A, "Incentive Conflicts and Contractual Restraints: Evidence from Franchising," *Journal of Law and Economics*, October 1999, *42* (2), 745–774.

Bureau, U.S. Census, 2007.

Charnes, A., W. Cooper, and E. Rhodes, "Measuring the Efficiency of Decision Making Units," *European Journal of Operational Research*, November 1978, *2* (6), 229–244.

_ , W. Lewin, and L. Seiford, eds, *Data Envelopment Analysis: Theory, Methodology, and Application*, Morwell, MA: Kluwer Academic Publishers, 2001.

Chen, Yao, Liang Liang, and Joe Zhu, "Equivalence in two-stage *DEA* approaches," *European Journal of Operational Research*, 2009, *193* (2), 600 – 604.

Cook, Wade D and Larry M Seiford, "Data envelopment analysis (DEA) – Thirty years on," *European Journal of Operational Research*, January 2009, *192* (1), 1–17.

Donthu, Naveen and Boonghee Yoo, "Retail ProductivityAssessment Using Data Envelopment Analysis," *Journal of Retailing*, 1998, *71* (1), 1–17.

Einolf, Karl W, "Is Winning Everything?: A Data Envelopment Analysis of Major League Baseball and the National Football League," *Journal of Sports Economics*, May 2004, *5* (2), 127–151.

Farrell, M J, "The Measurement of Productive Efficiency," *Journal of the Royal Statistical Society*, 1957, *120* (3), 253–290.

Gallini, Nancy T and Nancy A Lutz, "Dual Distribution and Royalty Fees in Franchising," *Journal of Law, Economics, & Organization*, October 1992, *8* (3), 1–32.

Hoff, Ayoe, "Second stage DEA: Comparison of approaches for modelling the DEA score," *European Journal of Operational Research*, 2007, *181* (1), 425 – 435.

Hwang, Shiuh-Nan and Te-Yi Chang, "Using Data Envelopment Analysis to Measure Hotel Managerial Efficiency Change in Taiwan," *Tourism Management*, August 2003, *24* (4), 357–369.

Ingene, Charles A, "Scale Economies in American Retailing: A Cross-Indutry Comparison," *Journal of Macromarketing*, 1984, *4* (2), 49–63.

Joo, Seong-Jong, Philipp A Stoeberl, and Kristin Fitzer, "Measuring and benchmarking the performance of coffee stores for retail operations," *Benchmarking: An International Journal*, 2009, *16* (6), 741–753.

Keh, Hean Tat and Singfat Chu, "Retail Productivity and Scale Economies at the Firm Level: a DEA Approach," *The International Journal of Management Science*, April 2003, *31* (2), 75–82.

Lafontaine, Francine, "Agency Theory and Franchising: Some Empirical Results," *The Rand Journal of Economics*, July 1992, *23* (2), 1–21.

_ **and Kathryn Shaw**, "The dynamics of franchise contracting: Evidence from panel data," *Journal of Political Economy*, October 1999, *107* (5), 1041–1080.

_ **and** _ , "1," *The Rand Journal of Economics*, 2005, *36* (1), 131.

_ **and Roger Blair**, *The Economics of Franchising*, Cambridge: Cambridge University Press, April 2005.

Liu, John S., Louis Y.Y. Lu, Wen-Min Lu, and Bruce J.Y. Lin, "A survey of DEA applications," *Omega*, 2013, *41* (5), 893 – 902.

Mathewson, G Frank and Ralph A Winter, "The Economics of Franchise Contracts," *Journal of Law and Economics*, October 1985, *28* (3), 1–25.

McDonald, John, "Using least squares and tobit in second stage DEA efficiency analyses," *European Journal of Operational Research*, 2009, *197* (2), 792 – 798.

Metters, Richard D, Frances X Frei, and Vincant A Vargas, "Measurement of Multiple Sites in Service Firms with Data Envelopment Analysis," *Production and Operations Management*, October 1999, *8* (3), 1–18.

Norton, Seth W, "Franchising, Labor Productivity, and the New Institutional Economics," *Journal of Instiutional and Theoretical Economics*, 1989, *145* (4), 578–596.

Piot-Lepetit, Isabelle, Rozenn Perrigot, and Gérard Cliquet, "Plural Form and Franchise Chains Efficiency: A DEA Meta-Frontier Approach Applied to French Chains," February 2012.

Ray, Subhash, "Resource-Use Efficiency in Public Schools: A Study of Connecticut Data," *Management Science*, December 1991, *37* (12), 1620–1628.

_ , *Data Envelopment Analysis: Theory and Techniques for Economics and Operations Research*, Cambridge: Cambridge University Press, June 2004.

Reynolds, Dennis, "Productivity Analysis In the On-Site Food Service Segment," *Cornell Hotel and Restaurant Administration Quarterly*, June 1998, *39* (3), 22–32.

_ **and Gary M Thompson**, "Multiunit Restaurant Productivity Assessment Using Three-Phase Data Envelopment Analysis," *International Journal of Hospitality Management*, March 2007, *26* (1), 20–32.

Rubin, Paul H, "The Theory of the Firm and the Structure of the Franchise Contract," *Journal of Law and Economics*, April 1978, *21* (1), 1–12.

Solis-Rodriguez, Vanesa and Manuel Gonzalez-Diaz, "How to Design Franchise Contracts: The Role of Contractual Hazards and Experience," *Journal of Small Business Management*, 2012, *50* (4), 1–26.

Zhang, Yun and Robert Bartles, "The Effect of Sample Size on the Mean Efficiency in DEA with an Application to Electricity Distribution in Australia, Sweden, and New Zealand," *Journal of Productivity Analysis*, 1998, pp. 187–204.

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