Franchising and Productivity in the Retail Establishment Sector

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Abstract

Franchising is a significant force in the American economy. As of the 2007 Economic Census, roughly ten percent of businesses are either a franchisee-owned business or are owned by a franchisor. While there has been significant research on the reasons for franchising, little work has examined the outcomes. This paper attempts to fill that gap. We employ a two stage process to determine how a business's productivity is impacted by being owned by a franchisee. The first stage uses data envelopment analysis to calculate each location's efficiency and obtain a ranking. These are then used as the dependent variable in Tobit regressions. Our results show that franchisee-owned stores in the retail trade sector rank higher and are more efficient than their franchisor-owned counterparts. We conclude by pointing out ways that our future research can build off of this paper.

1 Introduction

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 (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 corporation 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.

This paper seeks to deepen the understanding of how franchising impacts the actions of the manager. If companies, in fact, use franchising in order to mitigate the principal-agent problem, then companies that franchise should see higher sales, higher profit, and/or higher productivity. We present a method to compare productivity of franchised and non-franchised outlets. Using data envelopment analysis (DEA), we compute efficiency scores and rankings for a group of retail outlets. We then use regression techniques to see how franchising impacts these two measures. The current dataset, which we describe in section 3, leads us to imperfect results that show that franchisee-operated stores perform better than franchisor-operated stores. We also discuss how better data, which will be available to us soon, will likely strengthen these results.

2 Literature Review

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 and how being a franchised outlet impacts the value of the company. In this section, we give a broad overview of the research that has been conducted on franchising. We also give a review of the literature on measuring productivity in retail. After rejecting the some of the more common retail productivity measures, we argue for different measures using data envelopment analysis.

2.1 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 out across a geographically large region, it may be hard for the franchisor 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's incentive to shirk 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 rates that he is required to pay to the franchisor. This means that the 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 (Brickley, 1999; 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 will be some 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. In typical franchise contracts, the franchisee pays a portion of the sales to pay for advertising and a portion as a royalty (Lafontaine and Blair, 2005). 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, Lafontaine and Shaw 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 data availability.

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. Our paper is designed to fill that gap. Like Norton, we will be using productivity[1] as our measure of a store's performance. We 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 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 we 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 next subsection, we will turn our attention to the best way to go about measuring productivity in a retail context.

[1] In this paper, we will use productivity and efficiency interchangeably. This follows the DEA literature.

2.2 Productivity Measures

The literature on measuring retail productivity is extensive. While there have been numerous papers written on the topic, a commonly agreed upon measure has proven to be elusive (Achabal, Heineke and McIntyre, 1984; Reynolds and Thompson, 2007). In this section, we will examine some of this literature, detailing the more common measures. We conclude the section with a discussion of a more recently developed 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. The assumption, particularly in retail, is that labor is the best factor to use because it is the most important and largest factor of production (Reynolds and Thompson, 2007). 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.

There are issues with this approach, however, as Achabal et al. (1984) point out. Including sales in a productivity measure by definition is introducing demand into the calculation. It is very likely that this measure of productivity would change through no actual change in productivity. This measure would indicate an increase in productivity either if sales stayed the same and employment dropped (potentially a true increase in productivity) or if sales increased and employment stayed the same (more likely the result of increased demand). An amazing manager with an amazing team of employees could have very low sales if the product or the location was not good. Conversely, a terrible manager with lazy employees could see high sales if their product is popular. In both cases this measure fails to capture the true level of productivity achieved by the sales team. Further, productivity could potentially rise simply through inflation. Since revenue increases when either the price or the quantity increase, rising prices, even if they are simply due to inflation, would increase revenue. Using a ratio of some output measure to some input measure might work for more macro-level comparisons of aggregate retail productivity (Higón, Bozkurt, Clegg, Grugulis, Salis, Vasilakos and Williams, 2009), but they are not sufficient for measuring productivity within a firm (Reynolds, 1998).

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). When a consumer buys a product from a retailer, 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 (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.

The problem with total factor productivity, however, is that it requires prices in order to aggregate all inputs. This is not insurmountable for an input like labor which has a wage rate or for supplies that have a market price. But it poses a larger problem for inputs that do not have prices, such as experience or the number of parking places (Ray, 2004). While sales or revenue usually suffice as an output measure, for a retail context we might want to include other measures as well, such as customer satisfaction, which also does not have a price. Even if all inputs were in the same types of units (dollars or quantity), there would still be the problem of trying to determine the weight to place on each type of input (Metters, Frei and Vargas, 1999). It is likely not reasonable to assume that one employee is equal to one square foot of retail space or one cash register. It is also not reasonable to assume that one extra dollar spent on a worker bring exactly the same return as an extra dollar spent on a cash register. A total factor productivity based on total cost treats all dollars – and inputs – as perfect substitutes. One way around this is to include the cost of both types of inputs, but again that runs into the problem that prices are not always available. Also, if the industry is not perfectly competitive, price may not give a true indication of an input's value (Ray, 2004).

A possible solution to this problem is to weight the inputs. But this becomes difficult due to the necessary assumption that all establishments place the same value on labor as on capital. 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. In sum, while total factor productivity is appealing, there are significant drawbacks that make a search for an alternative worthwhile.

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). It calculates output to input ratios using shadow prices as the weights. Unlike total factor productivity, DEA allows for each location (or decision-making unit [DMU], in the language of the literature) to have different weights on inputs and outputs. These shadow prices are set so that each individual DMU has the highest possible efficiency score, given their inputs and outputs. Another distinguishing characteristic of DEA is that it uses the best performing DMUs as the basis on which all other DMUs are evaluated. These best performing stores earn an efficiency score equal to one. All other, less efficient, DMUs earn an efficiency score less than one. Mathematically, the goal of DEA is to (Metters et al., 1999):

$$\max_{u,v} \frac{\sum_{j=1}^{m} u_j y_{jk}}{\sum_{i=1}^{r} v_i x_{ik}} \tag{1}$$

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

In words, the output to input ratio for each DMU is maximized with respect to the weights, u and v, subject to the constraint that using DMU k's weights and DMU n's input and output data, the efficiency score will still be less than or equal to one. The linear programming behind DEA starts with the best performing (or more efficient) stores and then forces all other ratios to be lower. If they were not lower, the constraint wouldn't hold This means that the DMUs are compared with the best-performing units instead of the average unit.

While DEA certainly has some advantages over other methods of calculating productivity, there are a few limitations that should be pointed out. Because neither a production function nor a cost function is calculated, marginal productivities and costs are not derivable. Additionally, DEA is a linear programming technique, not a statistical technique. That means that t-stats can not be calculated and hypothesis tests can not be conducted on the output (Ray, 2004). This, however, is a larger problem when the results of the paper stop at the DEA scores. Our analysis uses the DEA output in regression analysis, which includes the standard statistical measures.

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 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. This is the only paper that we have seen that uses the output of data envelopment analysis as a dependent variable.

Finally, Botti, Briec and Cliquet (2009) use DEA to examine how franchising impacts 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 our work here, we depart from Botti et al. in two significant areas. First, 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. Second, 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. We believe that these two factors make this work a significant step beyond where they ended.

3 Data

3.1 Current Data

The data that we use in the present paper come from the Census Bureau's Survey of Business Owners Public Use Microdata Sample (SBO PUMS). The SBO PUMS dataset was created from the confidential responses of the 2007 Survey of Business Owners. The Census Bureau designed the SBO PUMS to allow researchers to conduct research using Census microdata without having to go through a lengthy approval process. To preserve confidentiality, the Census Bureau removed the name of the establishment, any identifying ID number, and reduced the each establishment's industry classification to the two-digit sector code. To add an extra layer of protection, the most sensitive information – the number of employees, payroll, and revenue – are rounded and noise is added. The exact method of doing this is not outlined, but a more detailed explanation of the methodology can be found on the Census Bureau's website[2].

The SBO PUMS also contains a wide variety of owner characteristics. Information on race, age, eduction, and whether managing the business is their main job, among other things, is reported for up to four different owners. Also included is information on how the business is operated, from the

[2] `http://www2.census.gov/econ/sbo/07/pums/2007_sbo_pums_users_guide.pdf`

language transactions are completed in to the type of employees employed. Of particular interest here is information on franchising. The survey mailed to businesses contains two yes-or-no questions related to franchising. The first is "In 2007, did this business operate as a franchise?" The second question is "In 2007, did a franchiser own more than 50% of this business?" The first question provides us with information on the establishments that are owned by franchisees and are operating as part of a franchised chain (e.g. a McDonald's owned by a franchisee). The second question is a bit harder to interpret. No explanation is provided to the people filling the survey out, so it is hard to know exactly what the Census Bureau is asking since "franchiser" is not a commonly used word. Since "franchisee" is a very commonly used term for someone who owns a franchise, the Census Bureau would have likely used that word if that is what they were referring to. Additionally, the first question already asks if an establishment is owned by a franchisee. Therefore, we interpret the second question as asking if the establishment is owned by a franchisor.

The SBO PUMS dataset contains information for a wide range of sectors, and we restrict our analysis to just two of them. We picked sectors 44 ("Retail Trade") and 72 ("Accommodation and Food Services"). Sector 44 contains car dealer ships, appliance stores, grocery stores, gasoline stores, and clothing stores, among others. Sector 72 contains restaurants, hotels, and camp grounds, among other things. Unfortunately, the SBO PUMS does not contain the third digit of an establishment's sector code, so we were limited in our analysis to the two-digit level.

Since our goal is to determine the effect of franchising on productivity, we want to compare establishments operated by a franchisee to establishments operated by a franchisor. To do this, we dropped all establishments from the data set that were owned by neither of these two groups. Additionally, there was a small number of establishments that were listed as being owned by both a franchisee and a franchisor. To avoid confusion in the OLS stage of the model, we eliminated these establishments as well. That left 8,529 establishments in sector 72 and 7,686 establishments in sector 44.

Summary statistics for the remaining establishments in sector 44 can be found in table 1. On average, franchisees operate larger establishments in all three categories measured in sector 44. In sector 72, franchisee-owned establishments have, on average, lower payroll than franchisor-owned shops.

One concern with this dataset, however, is that franchisee-owned establishments are vastly over-represented. The Census Bureau reports that 78% of franchise-related establishments are owned by franchisees. In this sample, over 95% are. One explanation for this is the odd wording of the franchise questions, making it possible that responders were confused about what the Census form was asking. It is also possible that corporate policies influenced how questions were answers by managers of franchisor-owned establishments. Whatever the reason, this is a cause for concern because it significantly over represents franchisees.

3.2 Ideal Data

A better source of data would include the name of the establishment and the sub-sector it operates in. This is important because it would allow for chain-level fixed effects. It is reasonable to assume that there are differences within chains that do not show up in observable data. For instance, different chains have different policies on how business should be conduced and may have different levels of autonomy for both franchisees and managers. That is not included in the observable data, but it is very important to how productive different establishments can be. Because of that, it is not fair to compare productivity of an establishment in one chain with an establishment in another chain directly. We have applied for, and are in the final stages approval for, confidential Census data. Once this new dataset is available to us, we will be able to control for characteristics that we are not able to control for here.

4 Empirical Methods

The empirical method used in this paper is a two-step process. Following the method employed by Reynolds and Thompson (2007), the first step in the process is to run the data envelopment analysis. As was described above in section 2.2, data envelopment analysis requires the specification of certain inputs and outputs. Reynolds and Thompson argue that it is best to use inputs that are not controllable by the manager. In other words, it is best to use things that are fixed in the short run. This is not feasible with the available data. The SBO PUMS data that are available contain two likely measures of inputs: payroll and employment. Neither of these measures are perfect, as they are both controllable by the firm's manager. However, more desirable input measures, such as square footage or location, are not available in the public use data. Employment is defined as the number of employees working at the business. Payroll is the amount of money spent on paying workers. The output chosen is also not optimal based on Keh and Chu's work. However, the only viable output measure in the available data is receipts, a measure of money brought in to the business from customers. All three of these three variables are noisy in order to preserve confidentiality.

The output from the DEA procedure (the efficiency score and the ranking) become two different independent variables in the second stage. In this stage, we run the following regression:

$$y_i = \beta_0 + \beta_1 \mathit{franchisee}_i + \mathbf{Z}_i\alpha + \gamma + \epsilon_i \tag{3}$$

where *franchisee* equals one if firm i is owned by a franchisee. Also included are a series of control variables, $\mathbf{Z}_i$, which includes characteristics about firm i, such as years in business, location, and information about the owner. It, however, does not contain any of the variables used in the DEA. In the present paper, we use the age of the establishment and the percent of the establishment owned by the largest owner.

The left hand side variable, y_i represents the rank and efficiency scores produced by DEA. Equation (3) is run twice, with each DEA output variable taking the place of y_i. When rank is the dependent variable we expect that β_1 will be negative. When the efficiency score is the dependent variable, we expect that β_1 will be positive. In other words, franchisee-operated stores should be more efficient than manager-operated stores. The signs are opposite of each other because a lower ranking is better and a higher efficiency score is better. Recall that the most efficient stores are given a ranking of one and an efficiency score of one. As stores become less efficient, their ranking increases and their score falls.

5 Results

The first step in the process is to run the data envelopment analysis. This produces two different outputs, a rank for each store and a efficiency score for each store. Since it would not be informative to list each store's results, a summary of the results of the DEA is in table 2.

The statistics in table 2 show that franchisee-owned establishments have a lower ranking, on average, than franchisor-owned establishments in sector 44 and higher average ranking in sector 72. Meanwhile, the average efficiency scores are virtually identical for sector 44 and is lower, on average, for franchisees in sector 72.

The next step is to run equation (3) using a Tobit model and the results are in tables 3 (for sector 44) and 4 (for sector 72). All specifications were also run as standard OLS regressions. Since OLS is not the best estimator in this situation, due to the upper and lower bounds on the left-hand-side, these results are omitted. For sector 44 – retail trade – franchisee ownership has a negative coefficient for rank and a positive coefficient for the efficiency score, both when control variables are included and not. The coefficient on franchisee ownership is significant in all three rank models, and and coefficient on franchisee ownership in the efficiency score models becomes significant when control variables are included. These results are as predicted.

Unfortunately, for sector 72 – food and accommodation services – the results are a mixture of insignificant coefficients and wrong signs. For all three layers of specification the signs are opposite of the expected results. None of the three specifications turn up significant results when rank is the dependent variable, and all three are positive. When efficiency is the dependent variable, franchisee ownership is significant in all three cases, but it has a negative coefficient. These are very curious results because they suggest that franchisees operate less productive establishments than franchisors do, which is contrary to the theory. There are various possible reasons for this, but it likely has to do with the wide range of establishments included in sector 72. Since sector 72 contains establishments from small restaurants to large hotels, it is unlikely that all establishments are comparable. This is likely the reason why the results for sector 44 are more in line with our predictions that sector 72. As table 1 shows, establishments in sector 72 cover a much larger employment spread than those in sector

44.

5.1 Matching Results

As we discussed above, data limitations prevent us from controlling for the type of establishment. As an imperfect substitute for subcategory fixed effects, we run a matching estimation for the effect of franchisee-ownership in sector 72. The matching estimation finds establishments that have a similar set of characteristics, and uses the franchisor-owned establishments as the base group and the franchisee-owned establishments as the treatment group. We matched the establishments using the DEA variables, which are payroll expenditures, the number of employees, and the revenue. This means that large hotels and small restaurants are not being compared when the effect of franchisee-ownership is calculated.

The matching results are in table 5. Whereas the Tobit results are insignificant and have incorrect signs, the matching results are more in line with what we expect. The coefficient for the rank is strongly significant in the downward direction, and the coefficient for the efficiency score is statistically significant in the upward direction. This tells us that, when we control for size, franchisee-owned establishments perform better, and are more efficient, than franchisor-owned establishments. As a test, we also run this analysis on sector 44, which performed better in the Tobit regressions, and present the results in table 6. The results are in line with the results that are in table 3. Our hypothesis for why sector 44 performs better in the Tobit regression than sector 72 does is that the establishments in sector 44 are more homogeneous than those in sector 72. If that is the case, we would expect that matching in sector 44 would be less beneficial than in sector 72. This seems to be borne out in the data.

One caveat to these matching results, and a key reasons why the full Census data set is needed, is that we are not able to control for any other characteristics of the establishment. In the Tobit regressions, we control for the age of the establishment and the ownership stake of the largest owner. The way the matching command in Stata works, we are prohibited from including anything in the model other than the dependent variable and the treatment – franchisee-ownership in our case. The results here, though, suggest that we will see confirmation of our hypothesis when we get access to the confidential Census data.

6 Conclusion

In this paper we presented a detailed literature review focusing on the topics of the principal-agent problem, measuring productivity in retail, and data envelopment analysis. We discussed how franchising is used by firms to try to mitigate the principal-agent problem. By giving the manager an ownership stake in the store that he manages, the franchisor gives the manager/franchisee an incentive to increase productivity and profits. This is because of the fact that increasing profits not only benefits the company but it also increases the manager-turned-franchisee's own income. We also discussed how measuring productivity is difficult in a retail context. Many papers have used partial factor productivity by looking at output per worker. This measure falls short because it only looks at one, albeit important, factor of retail production. Additionally, total factor productivity falls short because it requires financial figures and a universal weighting system. Therefore, we proposed using data envelopment analysis as a tool to calculate retail productivity. This process allows for multiple inputs and multiple outputs, and does not require that they be of the same type.

Using public-use Census data, we used data from NAICS sectors 44 and 72. Taking one sector at a time, we then used data envelopment analysis to calculate a ranking and efficiency score for each store in our sample. The last step in our empirical process was to run regressions using the DEA output as dependent variables. Our results show that franchisee-run stores have a lower (i.e. better-ranked) rank than franchisor-run stores in sector 44, but show the opposite for sector 72. We hypothesize that these contradictory results are more a function of bad data than any true differences in the sectors.

6.1 Future Research

Our future research will improve on these findings. As we discussed in section 5, our results are promising, but data limitations call them into question. This is due to the noise in put into the data to preserve confidentiality, the lack of identifying information (name, location, etc), a lack of the third and fourth digit of the NAICS sector code, and a lack of additional inputs. Our future research will include a better dataset. By gaining access to confidential Census microdata, we will have access to many of the elements omitted from the public data. This will allow for a better set of controls, and hopefully more meaningful conclusion to be drawn.

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Tables

	Sector 72					Sector 44				
	All Establishments					All Establishments				
	Mean	St. Dev.	Min	Max	N	Mean	St. Dev.	Min	Max	N
Employment	107.45	244.51	1	8700	8529	51.14	83.04	1	1800	7688
Payroll	1234.87	2712.74	10	69000	8529	1999.27	3709.69	10	94000	7688
Receipts	4645.85	98.45	10	240000	8529	26789.37	55691	10	1800000	7688
	Establishments Owned by Franchisees					Establishments Owned by Franchisees				
	Mean	St. Dev.	Min	Max	N	Mean	St. Dev.	Min	Max	N
Employment	107.66	245.2	1	8700	8515	52.02	83.69	1	1800	7502
Payroll	1232.34	2709.9	10	69000	8515	2036.65	3741.62	10	9400	7502
Receipts	4648.59	9885.84	10	240000	8515	27316.53	56201.73	10	1800000	7502
	Establishments Owned by Franchisors					Establishments Owned by Franchisors				
	Mean	St. Dev.	Min	Max	N	Mean	St. Dev.	Min	Max	N
Employment	92.46	187.33	1	1100	114	15.73	35.85	1	320	186
Payroll	1421.93	2921.41	10	17000	114	491.61	1358.51	10	12000	186
Receipts	4443.68	8609.02	40	51000	114	5527.04	18313.39	20	170000	186

Table 1: *Summary Statistics*

Franchisee-Owned Establishments				
	Sector 44		Sector 72	
	Rank	Efficiency Score	Rank	Efficiency Score
Mean	3821.52	0.053	4281.38	0.082
St. Dev.	2210.94	0.056	2441.49	0.059
Min	1	0.00065	1	0.007
Max	7688	1	8528	1
N	7502	7502	8075	8075

Franchisor-Owned Establishments				
	Sector 44		Sector 72	
	Rank	Efficiency Score	Rank	Efficiency Score
Mean	4760.24	0.052	4268	0.097
St. Dev.	2371.77	0.097	2998.42	0.088
Min	1	0.0011	19	0.017
Max	7687	1	8514	0.709
N	186	186	110	110

Table 2: *Summary of DEA results.*

LHS Variable	Rank	Efficiency Score	Rank	Efficiency Score	Rank	Efficiency Score
Constant	4760.24	0.052	5019.70	0.052	5518.02	0.042
	(162.38)	(0.0042)	(168.94)	(0.004)	(188.66)	(0.005)
Franchisee-Owned	−938.72***	0.0013	−889.74***	0.003	−982.26***	0.005*
	(164.38)	(0.0042)	(168.07)	(0.004)	(168.42)	(0.004)
Age			−18.28***	−0.0001***	−17.87***	−0.0002***
			(2.55)	(0.00006)	(2.55)	(0.00006)
Ownership % of largest owner					−5.99***	0.0001***
					(1.02)	(0.00002)
Pseudo R^2	0.0002	−0.0000	0.0006	−0.0002	0.0009	−0.0011

Table 3: *Tobit regression output for sector 44. Standard errors are in parentheses. For rank, lower is better. For efficiency, higher is better. ***=significant at the 1% level. **=significant at the 5% level. *=significant at the 10% level.*

LHS Variable	Rank	Efficiency Score	Rank	Efficiency Score	Rank	Efficiency Score
Constant	4268.8	0.097	4047.79	0.10	3938.39	0.11
	(233.55)	(0.0057)	(236.23)	(0.006)	(247.13)	(0.006)
Franchisee-Owned	12.58	−0.015***	35.64	−0.016***	45.94	−0.02***
	(235.13)	(0.0058)	(234.69)	(0.006)	(234.75)	(0.006)
Age			17.49***	−0.0006***	17.22***	−0.0005***
			(3.05)	(0.00007)	(3.05)	(0.00007)
Ownership % of largest owner					1.60	−0.00004
					(1.06)	(0.00002)
Pseudo R^2	0.0000	−0.0003	0.0002	−0.0027	0.0002	−0.0028

Table 4: *Tobit regression output for sector 72. Standard errors are in parentheses. For rank, lower is better. For efficiency, higher is better. ***=significant at the 1% level. **=significant at the 5% level. *=significant at the 10% level.*

LHS Variable	Rank	Efficiency Score
Franchisee-Owned	-729.63^{***}	0.009^{**}
	(196.6)	(0.005)

Table 5: *Matching estimation for Sector 72. Standard errors are in parentheses. ***=significant at the 1% level. **=significant at the 5% level. *=significant at the 10% level.*

LHS Variable	Rank	Efficiency Score
Franchisee-Owned	-390.04^{***}	0.003
	(168.02)	(0.008)

Table 6: *Matching estimation for Sector 44. Standard errors are in parentheses. ***=significant at the 1% level. **=significant at the 5% level. *=significant at the 10% level.*