

Franchise Contract Regulations and Local Market Structure*

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Abstract

Many U.S. states have regulations in place that restrict the ability of franchisors to terminate franchise contracts. We estimate the economic effects of these regulations, with a focus on how they impact market structure. Using data from the quick-service restaurant industry, we find that implementing the franchise regulation results in 4-5% fewer establishments in the average county. Our results imply franchise regulation leads to increased concentration in a large number of markets, as the number of counties in the bottom quartile of concentration would increase by between 11% and 15% with regulation.

KEYWORDS: Franchising, Entry, Regulatory Capture, Retailing

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1 Introduction

States commonly regulate markets with the justification of protecting consumers, local business owners, or both. The industries targeted and types of regulations vary from state to state, but examples of regulations and protected industries include occupational certification or licensing (e.g. from personal hairdressers to medical professionals), and antitrust exemptions for hospital systems, the insurance industry, educational institutions, alcohol retailers, car dealerships, and gas stations. The United States Department of Justice and Federal Trade Commission have recently focused on the potential anticompetitive effects of certain state regulations and the worry that these types of regulations represent regulatory capture by businesses.¹

In this paper, using the quick service restaurant as a case study, we examine the competitive effects of a common state regulation in franchised industries that restricts the ability of franchisors to terminate franchise agreements. These regulations, which are present in 16 US states, increase the potential costs to the franchisor of contracting with an entrepreneur by making it difficult to replace underperforming franchisees. The regulations have the support of lobbying groups representing franchisees with the stated goal of protecting local entrepreneurs against “opportunistic” franchisors by guaranteeing franchisees can operate long enough to recover fixed costs of relationship-specific investments. But the laws may constitute a form of regulatory capture by limiting entry by potential entrepreneurs, resulting in more concentrated markets.² Our contribution is to estimate the economic consequences of these franchise contract regulations, specifically focusing on how they impact local market structure.

We begin by specifying a parsimonious two-period model where a franchisor chooses how many franchised establishments to open in a market. Each establishment is run by an entrepreneur who can be either high or low quality, but the franchisor learns the entrepreneur type after some time. In unregulated markets, the franchisor can replace an entrepreneur

¹This includes focus by the FTC on occupational licenses and attention by the DOJ on state antitrust issues. For example, in 2018, the US Department of Justice hosted a series of round-tables on the relationship between regulation and competition. See <https://www.justice.gov/atr/CompReg>. Additionally, Federal Trade Commissioner, Joshua Wright, discussed the importance of considering regulatory capture in high-tech industries in a speech in 2016. See https://www.ftc.gov/system/files/documents/public_statements/634631/150402clemons.pdf. State occupational licensing was successfully challenged in *North Carolina State Board of Dental Examiners v. FTC*. This is a difficult area for federal competition authorities because generally state action is immune from antitrust liability according to the Parker immunity doctrine, *Parker v. Brown*.

²The franchise lobbying groups The Coalition of Franchisee Associations (CFA) and The American Association of Franchisees and Dealers address franchise terminations in their respective ‘Bill of Rights.’ See <https://thecfainc.com/universal-franchisee-bill-of-rights/> and <https://www.aafd.org/fairness-initiatives/franchisee-bill-of-rights/>.

after their quality is revealed at the end of the first period. In regulated markets, the entrepreneur drawn in the first period operates the establishments for both periods. The model suggests the franchisor will open fewer franchised establishments and fewer establishments overall in regulated markets, a prediction that we bring to the data.

We collect cross-sectional establishment level data for the five largest US national quick-service restaurant chains in 2012. Using these data, we estimate the relationship between the contract termination regulations and the number of establishments at the county-chain level. Results confirm the outcome of the model, as they indicate that the average chain has 9% fewer franchises and 8% fewer establishments (franchise plus corporate-owned stores) in regulated counties. Next, in order to make predictions about the impact of the regulations, we estimate a structural model of county-level entry that is based on the seminal work of Bresnahan and Reiss (1991) in order to account for the fact that observed entry patterns are the outcome of strategic interactions among competing chains. As in their work, the model is estimated using ordered probit, where the outcome is the number of total establishments in a county across all five chains. We further follow their work by analyzing small and medium sized markets – counties with a population less than 50,000, which represents 2,150 of 3,100 counties in our full sample.

The parameter estimates indicate that the regulations lead to more concentrated markets in equilibrium, as the likelihood we observe the outcome of four or fewer total establishments in a county is about 2% higher in regulated counties than unregulated counties. We then use the estimates of the model to perform two counterfactual exercises. First, we quantify the impact of enacting termination restrictions in counties that currently don't have them (1,443) and find that the establishments per capita would fall by about 4.8% in the average county. The number of markets with a low level of competition (in the bottom quartile of number of establishments per capita) increases from 226 to 252 (11%), while the number of markets with a high level of competition (in the top quartile of number of establishments per capita) decreases from 171 to 102 (40%). Second, we quantify the impact of removing restrictions in counties that currently have them (708). We find that the number of total establishments per capita increases by 4.6%, the number of markets with a low level of competition decreases from 54 to 46 (15%), and the number of markets with a high level of competition increases from 92 to 141 (53%). Put together, the results suggest that the regulations significantly impact local market structure in this industry, leading to more concentrated markets and a lower level of product variety available to consumers in terms of geographic differentiation.³

³Although we find that state franchise regulations are associated with fewer franchised establishments, the argument for these laws is that they encourage franchisees to make substantial relationship-specific investments, and could even attract a higher overall quality of entrepreneur to franchised industries. We cannot estimate this trade-off using our data. Sertsios (2015) shows that franchisors in states with termination

Our study is most closely related to the other research examining the effect of franchise contract regulations on organizational form decisions and the extent of franchising. In early literature, Brickley, Dark, and Weisbach (1991) provide a theoretical framework for qualitatively characterizing the costs or benefits of franchise contract regulation and show that the regulation has an ambiguous effect on the extent of franchising. The empirical analysis, which is performed both at the industry/state-level and at the establishment level, shows that a franchisor is more likely to open a company-owned store in states which have a regulation. The model we present in Section 2 has a similar flavor to one of the variants of their model in that we argue that regulations impose a cost to the franchisor and this cost results in fewer franchises. However, our analysis differs in that we examine how the regulations affect local market structure (i.e., the number of total establishments) rather than focus on the substitution between franchisee and company-owned establishments.⁴ Therefore, for the primary analysis, we do not decipher between these two types. In fact, the substitution between ownership types estimated in Brickley, Dark, and Weisbach (1991) works to dampen the effects of the regulation, as the reduction in franchises is partially offset by an increase in company-owned establishments.

In later work, Klick, Kobayashi, and Ribstein (2012) use changes to franchise regulations in Iowa and Washington, DC in the 1990s to show that the number of franchised establishments for two large quick service restaurant chains (Domino’s and Burger King) decreases when the regulations are introduced. Their data allow them to utilize time series variation and a differences-in-differences empirical strategy, rather than the cross-sectional analysis done in Brickley, Dark, and Weisbach (1991). While we rely on cross-sectional variation, our analysis differs from Klick, Kobayashi, and Ribstein (2012) in a few important ways. First, our data are from more chains (five versus two) and include McDonalds and Subway, the two largest franchisors in the world.⁵ Second, because our focus is to estimate the impact of the regulations on local market structure, we analyze outcomes at the county-level rather than the state-level. This allows us to include a rich set of county-level characteristics and to control for the effect of local competition, thereby accounting for heterogeneity in entry decisions within a state. Finally, we estimate a structural model of entry, which facilitates the

regulation require higher up-front payments from franchisees.

⁴There is a rich literature that focuses on the ownership structure of franchises outside the context of termination regulation, for example Lafontaine and Shaw (2005), Kosová, Lafontaine, and Perrigot (2013), and Nishida and Yang (2018).

⁵Klick, Kobayashi, and Ribstein (2012) uses McDonald’s data to examine the effect of a franchise regulation repeal in Washington, DC, but data restrictions do not allow them to examine the impact of the regulation change in Iowa. The results generally do not indicate that the DC repeal had an impact on franchising, something the authors attribute to the ease at which chains could contract around the regulations prior to the repeal.

counterfactual analysis quantifying the equilibrium effects of the regulation while accounting for strategic decisions of rival chains.

In more recent work, Sertsios (2015) extends the focus beyond the regulations' impact on the extent of franchising decisions and studies how the regulations affect the upfront investment requirements of franchisees. The results indicate that, in states that implemented franchise regulation in the 1970s, franchisors asked for larger up-front payments from franchisees.

More generally, our paper is related to the literature focused on the incentives in franchising and vertical contracts. Early theoretical work by Caves and Murphy (1976) and Rubin (1978) first connected the idea of franchising to agency problems. Since then, the dominant way franchising has been viewed by economists is through the lens of agency theory and downstream moral hazard, as in early empirical work by Lafontaine (1992). For a more recent review of downstream moral hazard and many related empirical papers that study franchising and vertical contracts more generally, see Lafontaine and Slade (2007) .

Finally, there are other studies that examine the effects of state regulations on competition and welfare. Blass and Carlton (2001) and Hastings (2004) examine contract divorce laws for gas stations, Kleiner and Krueger (2010) examine state occupational licensing, Houde, Newberry, and Seim (2017) examine the impact of state 'nexus' sales tax laws on e-commerce, and Murry (2018) examines franchise termination regulations specific to car dealerships.

The remainder of the paper is organized as follows. In Section 2, we introduce the theoretical framework. Section 3 introduces the data and is followed by a presentation of the empirical strategy and a discussion the main results in Section 4. Finally, Section 5 concludes.

2 A Model of Franchising Decisions and Contract Regulation

The [International Franchise Association] and others argue that equity protection for the franchisees will hinder the franchisor's ability to expand strategically and could affect quality and consistency if the company is not able to close underperforming stores or terminate franchisees who are not maintaining standards.⁶

In this section, we develop a two-period model of a chain's franchising decisions in order

⁶See "The Legal Issues That Could Change Franchising Forever," Entrepreneur Magazine 1/8/2015, <https://www.entrepreneur.com/article/240709>, accessed on 3/25/2017.

to motivate our empirical analysis. Specifically, the model provides a framework for how to think about the profitability of a franchisor and how it varies across locations with and without contract regulation, leading to the different outcomes that are observed in the data. Each period represents the term length of a franchise contract. Before the first period, the chain decides how many establishments to open in a local market, where each establishment is run by an entrepreneur (franchisee). The revenue earned by each establishment in each period is a function of the quality of its entrepreneur, which is unobserved by the chain *ex ante*. During period one, the revenue of each of the establishments is realized, of which the chain earns a (fixed) share through a royalty rate. Before the start of the second period, the chain may have the option to fire any entrepreneur and hire a new one to operate a specific establishment, where the ability to fire depends on the whether or not there are contract termination restrictions in place. Finally, during period two, revenues of each establishment are again realized.

To simplify the exposition, we assume that the quality of each entrepreneur is either high ($\tau = h$) or low ($\tau = \ell$) and that there is a share of ϕ high quality entrepreneurs in the population. The realized market structure in a given market is then a tuple indicating the number of establishments managed by each type: $\mathcal{M} = \{N^h, N^\ell\}$. We denote the per period revenues from an establishment managed by type τ as $R_{\mathcal{M}}^\tau$, which is a function the market structure through the competitive effects of other establishments, and the share of revenues earned by the franchisor is given by $\gamma \in (0, 1)$. Finally, there is a fixed operating cost for each establishment given by f which is known to the franchisor at time period 0. We assume that f is drawn for each market from a common distribution given by F_f .

When there are no termination restrictions in place, the chain has the option to fire a low quality entrepreneur. The franchisor will always take this option because it is costless to hire a new entrepreneur who might be a high quality type. Therefore, the *expected* profit of choosing N establishments in this unregulated (U) environment is:

$$\begin{aligned}
E[\pi^U(N)] = & \gamma \sum_{n=0}^N \underbrace{\Phi(N, n)}_{Pr(\mathcal{M}=\{N-n, n\})} \left(\underbrace{\left((N-n)R_{(N-n, n)}^h + nR_{(N-n, n)}^\ell \right)}_{\text{Period 1 Revenues}} \right) \\
& + \underbrace{\sum_{r=0}^n \Phi(n, r) \left((N-r)R_{(N-r, r)}^h + rR_{(N-r, r)}^\ell \right)}_{\text{Period 2 Revenues}} - 2Nf \quad (1)
\end{aligned}$$

where $\Phi(N, n)$ is the probability of drawing n low quality entrepreneurs when the chosen number of establishments is N . Under the binomial distribution with parameter ϕ , this is

given by:

$$\Phi(N, n) = \frac{N!}{n!(N-n)!} \phi^{N-n} (1-\phi)^n$$

The second term of Equation 1 represents the option value of the ability to fire the n entrepreneurs who are revealed to be low quality. In the regulated (R) environment, the franchisor cannot fire the low quality entrepreneur, so the expected value of choosing N establishments is:

$$E[\pi^R(N)] = 2\gamma \sum_{n=0}^N \Phi(N, n) \left(((N-n)R_{(N-n,n)}^h + nR_{(N-n,n)}^l) \right) - 2Nf. \quad (2)$$

Our goal is to demonstrate that the franchisor is more likely to choose a larger N in an unregulated environment. For this, it is sufficient to show that:

$$E[\pi^U(N+1)] - E[\pi^U(N)] > E[\pi^R(N+1)] - E[\pi^R(N)]$$

The term on the right hand side, which is the benefit of adding an additional establishment in the regulated environment, can be expressed as:

$$E[\pi^R(N+1)] - E[\pi^R(N)] = \sum_{n=0}^N 2\gamma (\phi H(n; N) + (1-\phi)L(n; N)) \quad (3)$$

where $H(n; N)$ is the value of adding adding an establishment run by a high quality entrepreneur when there are already n and $N-n$ low and high quality entrepreneurs in the market, respectively:

$$H(n; N) = R_{(N-n+1,n)}^h + (N-n)(R_{(N-n+1,n)}^h - R_{(N-n,n)}^h) + n(R_{(N-n+1,n)}^l - R_{(N-n,n)}^l)$$

The first term of this expression is the revenue from the additional establishment, while the second and third term are the lost revenue of the other N establishments from competing against the additional establishment. Equivalently, $L(n; N)$ is the value of adding an establishment with a low quality manager. The franchisor will choose to add an additional establishment in the regulated environment as long as:

$$E[\pi^R(N+1)] - E[\pi^R(N)] > 2f$$

meaning that the probability of adding a store before the realization of f is:

$$P^R(N) = F_f \left(\frac{\pi^R(N+1) - \pi^R(N)}{2} \right)$$

In the unregulated environment, the benefit of adding an additional establishment is:

$$E[\pi^U(N+1)] - E[\pi^U(N)] = \sum_{n=0}^N \gamma \left(\phi 2H(n; N) + \underbrace{(1-\phi) \left(L(n; N) + \phi H(n; N) + (1-\phi)L(n; N) \right)}_{\text{Benefit from the option to fire}} \right) \quad (4)$$

The difference between this expression and the expression for the regulated environment is the second term in the parentheses, which is the expected profit if the additional establishment is run by a low quality entrepreneur in the first period. The franchisor fires this entrepreneur and hires a new one, which is high quality with probability ϕ . The franchisor will choose to add an additional establishment in the unregulated environment as long as:

$$E[\pi^U(N+1)] - E[\pi^U(N)] > 2f$$

meaning the probability of adding a store in the unregulated environment before the realization of f is:

$$P^U(N) = F_f \left(\frac{\pi^U(N+1) - \pi^U(N)}{2} \right)$$

Taking the difference between Equation 4 and Equation 3 results in:

$$\begin{aligned} & \left(E[\pi^U(N+1)] - E[\pi^U(N)] \right) - \left(E[\pi^R(N+1)] - E[\pi^R(N)] \right) \\ &= \gamma \phi (1-\phi) \sum_{n=0}^N \Phi(N, n) (H(n; N) - L(n; N)) \end{aligned}$$

which is positive under the assumption that the value of adding a high quality establishment is always better than adding a low quality establishment.⁷ Therefore, the probability of adding an additional store is higher in the unregulated environment than the regulated environment at all levels of N :

$$P^U(N) > P^R(N)$$

This suggests that we are likely to observe more franchises in unregulated markets, an implication that we take to the data in Section 4. Another outcome of interest, which is the primary focus of our structural analysis, is the total number of establishments. Although not modeled here, previous literature has shown that there is substitution to company-owned establishments in regulated markets. However, as long company-owned establishments are

⁷This might not be true if the competitive effects of adding high quality establishments are large.

not perfect substitutes for franchises, then this would only dampen the impact of the regulations on the total number of establishments and not eliminate it. Therefore, under the assumption of imperfect substitutes, another implication of the model that we bring to the data is that the regulations result in fewer establishments overall.⁸

3 Data

Our empirical analysis focuses on the quick service restaurant industry. Quick service restaurant franchises (i.e., fast food) comprise over 20% of the top 500 franchises according to industry sources.⁹ It is estimated that these restaurants generated \$570 billion globally and \$200 billion in the United States in 2015.

We collect data on five of the top franchises in this industry: McDonald’s, Subway, Burger King, Wendy’s and Taco Bell. We construct a cross-section of all establishments that were open in 2012 for these five chains from data provided by a private firm, AggData.¹⁰ These data feature a list of the addresses of all stores listed on each chain’s website in late 2012, or early 2013. The second column of Table 1 reports the total counts of establishments listed by AggData, broken down by chain. Subway is the largest franchisor with over 25,000 establishments, followed by McDonalds with about 14,000. Burger King, Wendy’s, and Taco Bell are much smaller, with between 6,000 and 7,000 establishments nationwide.

To make sure that our sample is representative, we compare the total number of establishments in our sample to the counts provided by each chain in their 2012 Annual Report (last column of Table 1). Note that Subway is owned by a private company so they do not produce an annual report. The AggData count is smaller than the count in the annual reports for both McDonald’s and Burger King, but bigger for Wendy’s and Taco Bell. This is likely due to the nature of the data collected by AggData versus the annual statements, as AggData collects their list at a single moment in time and the financial statements cover an entire year. However, these differences are relatively small, maxing out at around 7%, suggesting that the AggData sample has good coverage.

We also collect the franchise status for each establishment, where the status indicates

⁸We note that the model also predicts that there is heterogeneity in the impact of the regulation based on royalty rates, the marginal benefits of entrepreneur quality, and the distribution of entrepreneur quality in the population. Because we do not directly observe measures of these, we leave an analysis of this heterogeneity for future work.

⁹Source: <https://www.entrepreneur.com/article/240720>

¹⁰Klick, Kobayashi, and Ribstein (2012) use within-state variation to identify the effect of the regulations. We do not take this approach for two reasons. First, AggData only provided us with a single year of data. Second, there are not any recent changes in the regulation that we are aware of (Klick, Kobayashi, and Ribstein (2012) use changes from the 1990s). The fact that our estimates (Table 3) are close to that of Klick, Kobayashi, and Ribstein (2012) is reassuring.

whether or not it is owned by a franchisee or the corporation. This information is not available in the AggData, but a list of the addresses for all the establishments that are franchised is reported in each chain’s annual Franchise Disclosure Documents (FDD). A FDD is the contract between the franchiser and franchisee. In many states, franchisors are required to report their FDDs to a government agency that, in turn, posts them on-line in portable document format. We collect the 2012 FDDs from the Minnesota Commerce Department.¹¹ The counts of franchises in the FDDs are displayed in the first column of Table 1. Not surprisingly, when we compare these figures to the data from the financial statements (second to last column), we see that the patterns in the franchised establishments mirror those of total establishments.

In order to determine the status of each establishment, we merge the FDD data with the AggData sample. Specifically, we define the collection of all establishments, both franchised and company-owned, as the list of provided by AggData. We define an establishment as franchised if it appears in both the AggData and in the FDD. In order to determine the intersection of these two lists, we merge them using multiple methods.¹² The matched sample is displayed in the middle two columns of Table 1. In theory, every address in an FDD should also be listed in the list provided by AggData but, as seen in the table, we do not get a 100% match for two reasons. Similar to what was previously mentioned, the timing of the data collection across the sources may not coincide. Second, there could be mistakes in how the raw lists are collected and merged. This is especially true for the FDD’s that are read from hard-copies by an optical scanner.

Finally, comparing our final (post merge) sample with the information from the financial statements suggests some differences between our sample and the reported numbers, but the differences are not large in magnitude. However, one might worry that these differences are due to mistakes in our raw data and/or problems with the merging the two data sources. The fact that these patterns also exist when comparing the pre-merged raw data and the data in the annual reports suggests that these discrepancies are likely due to differences in the timing of the data collection and do not reflect a data quality issue.

Overall, the information gathered suggests that franchisee’s own a majority, if not all, of the establishments for any particular chain. The smallest share of franchised establishments is about 78% (Wendy’s), while the largest is 100% (Subway). McDonald’s franchises almost 90% of their establishments. The high propensity to franchise, which can be due to a number

¹¹Source: <https://mn.gov/commerce/industries/securities/franchises/>.

¹²First, we match common variables in both lists such as store phone number, zip code, and address. Second, we geo-code each address using MapQuest and Google Maps API and merge on latitude and longitude (at different levels of precision). Finally, we hand check those addresses that did not match and manually match them to provide the most complete coverage as possible.

of reasons, implies that the termination laws are likely an important factor in determining the profitability of a chain.

Table 1: Establishments by Chain

Chain	FDD	AggData	Post-Merge Sample		2012 Annual Report	
	Franchised	Total	Franchised	Total	Franchised	Total
McDonald's	12,601	14,062	12,190	13,874	12,605	14,157
Burger King ^a	6,895	6,981*	6,895	6,981	7,293	7,476
Wendy's	5,564	6,200	5,224	6,116	4,528	5,817
Taco Bell	4,846	6,160	4,809	6,145	4,670	5,695
Subway	0	26,228	0	26,228	–	–

Notes: The * indicates that this information comes from Burger King's FDD rather than AggData. The Burger King report does not separate Canadian establishments from United States establishments, so this information includes 293 total stores in Canada. Subway is a privately owned company and does not publish financial information, including the total number of stores. Sources: Company FDD's, AggData, and company 10Ks.

3.1 Franchise Contract Regulations

States started to enact franchise termination regulation in the early 1970's following concerns about franchisor opportunism (Klick, Kobayashi, and Ribstein (2009)). Specifically, franchisees (and regulators) worried that, if they were able to easily terminate contracts, franchisors would use franchising as a tool to learn about and take over the most profitable locations. Nicasastro (1993) discusses this specific issue in the context of *Kealey Pharmacy v. Walgreen Co.* To restrict this type of action, the most basic form of the regulation requires the franchisor to have “good cause” for terminating a contract. Often times, franchisors will claim that “good cause” comes in the form of a breach of the franchise agreement by failing to make payments, failing inspections, putting the trademark in jeopardy, etc. However, the terminology “good cause” is typically left vague without specific definition in many of the regulations and its meaning is a primary point of argument in franchise litigation.¹³ Nicasastro (1993) provides an excellent overview of the different views behind the “good cause” provision and lists numerous examples of how it has been litigated in wrongful termination cases.

In theory, no matter which state they are located in, a franchisee can file a suit against the franchisor if they feel that their contract was wrongfully terminated. In practice, the “good cause” language makes defending the termination more difficult for the franchisor. Thus,

¹³For example, a 7-11 franchisee in New Jersey recently lost a case in which he claimed that his contract termination was without good cause. See <https://franchiselaw.foxrothschild.com/tags/new-jersey-franchise-practices-act/>

the regulation can be a valuable tool to the franchisee in presenting and winning a case for wrongful termination, and winning such a case can result in a large monetary settlement.¹⁴ The importance of these regulations to franchisees is further evidenced by the fact that the laws are regularly backed by franchisee lobbying groups like the American Association of Franchisees and Dealers (AAFD) and the Coalition of Franchisee Associations (CFA), citing the need to protect franchises from large franchise corporations.¹⁵

The wrongful termination cases and the laws that impact them are also an important concern for franchisors. Indeed, a lawyer representing McDonald’s Corporation cited wrongful termination as the most common claim asserted by franchisees and also mentioned the termination statutes as an important issue that comes up in the defense of these claims in a presentation at the 2019 International Franchise Association Legal Symposium.¹⁶

We collect the regulatory statuses of each state from Klick, Kobayashi, and Ribstein (2009).¹⁷ As of 2012, 16 states had some form of franchise termination regulation. All 16 states have the “good cause” provision for contract termination, but some have added additional provisions such as “good cause” for non-renewal of the contract and the “right to cure” the cause within a specified time-frame. Therefore, the “good cause” provision is the most basic form of the regulation, which we focus on for the remainder of the paper. In recent years, there has been a push to pass similar legislation in additional states and at the federal level.¹⁸

In Figure 1, we display a map of the contiguous states (in gray) that have the termination regulation. The regulations are mostly concentrated in the middle of the country, especially in the north, but there is additional coverage in heavily populated states on the coasts (e.g., California, New Jersey and Connecticut).

3.2 Additional Data

We also collect data to control for factors other than franchise regulations that may affect a franchisor’s decision to enter a local market. First, we obtain demographics such as pop-

¹⁴The law firm Dady and Gardner, P.A., which specializes in franchise law and is located in a regulated state (MN), cites numerous wrongful termination cases in which their clients received multi-million dollar payouts. See <https://www.dadygardner.com/big-wins/termination/>.

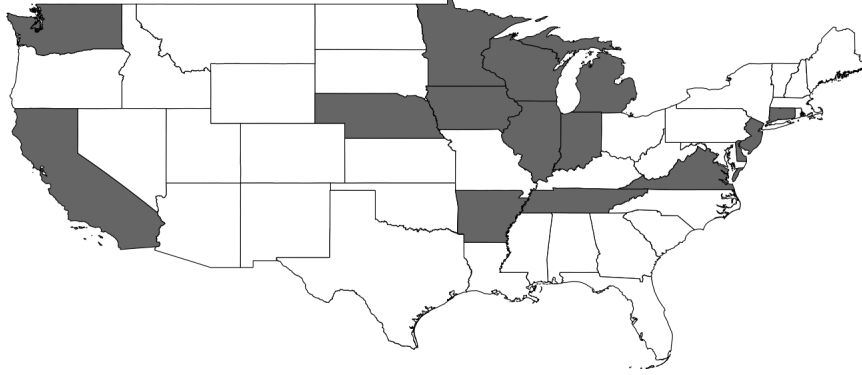
¹⁵See <https://www.entrepreneur.com/article/236565>.

¹⁶See https://www.franchise.org/sites/default/files/2019-05/BasicsTrack_FranchiseLitigation_0.pdf.

¹⁷To the best of our knowledge, the information in Klick, Kobayashi, and Ribstein (2009) are updated up to the early 2000s. We searched extensively for states that may have changed their regulation status between the early 2000s and 2012 and did not find evidence that any changes occurred.

¹⁸See https://www.dlapiper.com/en/us/insights/publications/2013/11/states-propose-revising-the-relationship-between_/ and <https://www.congress.gov/bill/115th-congress/house-bill/470/text>

Figure 1: States with “Good cause” Termination Regulation



Notes: States shaded in gray are states with ‘good cause’ regulations. Alaska and Hawaii, which are omitted in the interest of space, do not have ‘good cause’ regulations. Source: Klick, Kobayashi, and Ribstein (2009).

ulation and the median income for all of the counties in the United States in 2012 using publicly available data from the US Census Bureau. We merge this with county-level wage data for the fast-food industry, available from the Bureau of Labor Statistics. Second, similar to Brickley and Dark (1987) and Kosova and Sertsios (2018), we proxy for franchisor monitoring cost using the distance from the establishment to the chain’s headquarters. In order to determine this, we collect the location of each chain’s headquarters from the chain’s website and calculate the driving distance from this location to each establishment using the MapQuest API. Third, we collect information on whether or not the county has an interstate highway passing through it in order to control the importance of repeat customers from the County Business Patterns dataset. Finally, we collect the ranking of each state’s ‘access to capital’ published by CNBC, where 1 is the best state and 50 is the worst.¹⁹ The idea is that the pool of local entrepreneurs, both in quantity and quality, might be impacted by how easy it is to obtain the capital requirements to open a franchise.²⁰

3.3 Descriptive Statistics

Table 2 presents descriptive statistics for our full sample. The first panel presents the chain-level average establishment counts across counties, both in absolute and per-capita terms. Additionally, we break down the per-capita averages by regulation status. There is an average of 3.8 total establishments and 3.6 franchised establishments per-chain per-county, which implies about 93% of establishments are franchised in the average county. When

¹⁹Data accessed from <https://www.cnbc.com/id/100016697>.

²⁰To open a franchise, the franchisee typically needs to pay substantial startup costs that include a fixed payment to the franchisor and the funding for the purchase of equipment. Typically, franchise contracts specify an asset level for new franchisees.

controlling for population, the franchised share per-capita lowers to 90%, suggesting that franchisor-owned stores are in more populated areas. The patterns across regulated and unregulated states provides preliminary evidence that the termination laws impact market outcomes, as both the total number establishments and the number of franchises per capita are lower in regulated states.

In the second panel, we focus on the other control variables (at the county-level). Note that we omit the access to capital because it is a rank variable. About a third of the counties in the United States are subject to the termination restrictions, which suggests that the regulations are not concentrated in states with a relative large or small number of counties (i.e., 16/50 states = 0.32). Many of the restaurants are far away from the franchisor’s headquarters, as the average distance to HQ is almost 1,000 miles. This is about the same distance as a drive from Boston to Chicago. The median annual wage for a worker in this industry is quite low at \$12,600 and less than half of the counties in the US have an interstate running through them.

4 The Impact of Franchise Contract Regulations

In what follows, we estimate the relationship between the contract regulations and local market structure. We begin with a reduced-form analysis in which we determine the impact the regulations on the number of establishments for each chain in each county, while controlling for competition and other local covariates. We then specify and estimate a structural model of chain entry in order to predict the equilibrium effects of the regulations, focusing on their role in determining county-level market structure.

4.1 County-level Regressions

To determine the impact of the termination regulation on chain-level entry decisions, we regress the count of establishments (logged) for each chain on the county regulation status, as well as county and chain characteristics.²¹ The other county-level controls we include are (logged) population, land area, mean income, average wage of a quick service restaurant employee, and the distance from the county centroid to the chain headquarters. We also include a state-wide measure of entrepreneurial access to capital (ranking, 1-51), a dummy variable indicating whether or not an interstate highway passes through the county, a fixed effect for each census-region, and a fixed effect for each chain.

²¹We adjust the dependent variable by one to account for the zeros. We estimate the regressions using an arctangent approximation with similar results.

Table 2: Summary Statistics, Full Sample

Variable	Mean	Q25	Median	Q75
<i>Outcomes</i>				
Franchises	3.57	0	1.00	3.00
Total	3.83	0	1.00	3.00
Franchises per capita (10k)	0.40	0	0.24	0.57
Total per capita (10k)	0.42	0	0.26	0.59
<i>Unregulated States</i>				
Franchises per capita (10k)	0.41	0	0.23	0.55
Total per capita (10k)	0.42	0	0.25	0.57
<i>Regulated States</i>				
Franchises per capita (10k)	0.39	0	0.26	0.60
Total per capita (10k)	0.41	0	0.28	0.61
<i>Controls</i>				
Regulation	0.33	–	–	–
Dist to HQ	1,069	592	956	1,454
Population	96,773	10,765	25,644	66,294
Mean HH Income	56,195	47,514	53,751	61,625
Area, Sq. Miles	15,132	2,440	4,672	9,927
Mean Wage	13,634	11,071	12,601	14,325
Interstate Highway	0.44	–	–	–

Notes: The unit of observation for the first three rows is a chain-county. The unit of observation for the last six rows is a county. There are about 3,100 county and 15,500 chain-county observations. Source: US Census Bureau, Company 10Ks and FDDs, and AggData.

Before discussing the the county-level results, we point to the state-level results in the right side of Table 3, which provide a comparison to the analysis of Klick, Kobayashi, and Ribstein (2012).²² Recall that Klick, Kobayashi, and Ribstein (2012) uses panel-data in order to identify the effect of within-state changes in the regulation status, while we rely on cross-sectional variation. The dependent variables in these regressions are the (logged) number of franchises (5) and total establishments (6) for a chain in a state. We find that there are 8.3% fewer franchises and 5% fewer total establishments for a chain in regulated states. These are comparable to the estimates in Table 2 of Klick, Kobayashi, and Ribstein (2012), as they find that the a law changes in Iowa and Washington, DC resulted in 8% fewer franchised units for Burger King in these markets. However, we note that our estimates are

²²State-level population is the sum of the population of all counties within a state, while the other controls are the population weighted averages across counties in a state. The exception is the interstate variable, which indicates the total number of counties in the state with at least one interstate running through it.

not significant at the 5% level.

We now discuss the county-level results presented in specifications (1)-(4) of Table 3. For these regressions, all standard errors clustered at the county-level. An advantage of the county-level approach this is that we are able to control for within-state heterogeneity in observables and the impact of local competition. There are four specifications that differ in their dependent variable and whether or not we control for competition from other chains. First, focusing on the results of specifications (1) and (3), which ignore the impact of competition, we estimate that the regulations result in about 5.9% fewer franchises and 6.2% fewer establishments per-chain, overall. The coefficients are precisely estimated, which highlights the importance of controlling for county-level heterogeneity. However, by omitting competition, we are likely introducing bias into our estimate. Specifically, if the regulation implies fewer establishments, then it may be attractive for chains to enter regulated markets to avoid competition. This suggests the effects of specifications (1) and (3) are biased towards zero. The state-level estimates in (5) and (6) suffer from this critique as well.

Therefore, to capture the impact of competition, we estimate specifications where we include the total number of rival quick service establishments (logged) from the other four chains (a.k.a., ‘rivals’) as a regressor. As is common to this type of analysis, we have an endogeneity problem: the number of rival establishments is likely correlated with the error in our regression. For example, if a county is attractive to a particular chain for unobservable reasons, then we would expect it is also attractive to rivals for the same reasons. To address this issue, we instrument for the number of rivals using the distance-from-HQ variable (logged) for the rival with the shortest distance. Our assumptions for the validity of this instrument are that (a) the HQ distance for rivals does not directly affect the chain’s payoff from entering and (b) the shortest distance among rivals is a strong predictor of the total number of rivals. The results of the first-stage regression indicate that (b) is true, as the impact of the closest rival’s distance to HQ is negative and significant at the 1% level. Specifically, the estimate indicates that the number of rivals decreases by 3.6% for a 1% increase in distance (i.e., the coefficient is 0.036 and the standard error is 0.012).

The second stage results (specifications (2) and (4) in Table 3) indicate the correct sign on the effect of rivals. These effects are not significant, though we suspect that the significance would improve with the strength of the instrument. Importantly, controlling for the impact of competition results in a larger (in absolute value) effect of termination regulations, which confirms an omitted variable bias in specifications (1), (3), (5) and (6). The magnitude of the estimates imply that the number of franchises per chain is about 9.1% lower and the number of establishments per chain is about 8.1% lower in counties that are regulated, and these effects are significant at the 5% level, suggesting that counties in regulated counties

Table 3: Impact of Regulations on the Number of Establishments

	County-Level				State-Level	
	Log Franchises		Log Total		Log Franchises	Log Total
	(1)	(2)	(3)	(4)	(5)	(6)
Regulation	-0.059 (0.013)	-0.091 (0.032)	-0.062 (0.014)	-0.081 (0.026)	-0.083 (0.057)	-0.050 (0.055)
Number of Rivals		-0.885 (0.551)		-0.520 (0.451)		
Log Population	0.481 (0.009)	1.187 (0.444)	0.508 (0.009)	0.922 (0.363)	1.016 (0.032)	1.016 (0.032)
Log Median Inc.	-0.279 (0.072)	-0.700 (0.317)	-0.283 (0.078)	-0.530 (0.258)	-0.322 (0.109)	-0.398 (0.108)
Log Land Area (sq. mi.)	0.019 (0.007)	0.007 (0.015)	0.013 (0.007)	0.007 (0.013)	-0.050 (0.020)	-0.037 (0.019)
Log Wage	0.257 (0.028)	0.443 (0.132)	0.276 (0.030)	0.385 (0.107)	-0.652 (0.116)	-0.555 (0.115)
Access to Capital	-0.003 (0.001)	-0.006 (0.002)	-0.003 (0.001)	-0.004 (0.002)	0.002 (0.002)	-0.000 (0.002)
Log HQ Distance	-0.073 (0.010)	-0.071 (0.019)	-0.068 (0.010)	-0.067 (0.015)	-0.249 (0.096)	-0.225 (0.100)
Interstate Highway	0.156 (0.014)	0.372 (0.137)	0.171 (0.015)	0.298 (0.112)	0.083 (0.057)	0.075 (0.056)
Constant	-3.396 (0.702)	-6.241 (2.366)	-3.835 (0.758)	-5.505 (1.925)	1.217 (0.887)	0.932 (0.917)
R ²	0.778	0.487	0.801	0.665	0.637	0.651
Observations	15415	15415	15415	15415	250	250

Notes: Dependent variable is log establishments (plus adjustment) on regulation dummies and other covariates. For columns (5) and (6) the unit of observation is a state-chain in 2012. In columns (1)-(4), unit of observation is county-chain in 2012. All regressions include Census region effects and chain effects. Robust standard errors clustered at the county-level are presented in parenthesis for specifications (1)-(4). Robust standard errors presented in columns (5) and (6).

are more concentrated.²³ Further, the fact that the change in total establishments is less than the change in franchises implies there is a substitution effect between franchisee and company-owned establishments, which was studied by Brickley, Dark, and Weisbach (1991), among others. Specifically, the difference means that some of the reduction in franchises is made up for by the chain opening their own establishments. Although the difference in these coefficients is not statistically significant.²⁴

The results also indicate that counties with a higher population and those with an interstate, which are proxies for demand, have more establishments. Counties with higher

²³We highlight two variations of these regressions that we have run. First, we estimated Poisson regressions, with the count of establishments being the dependent variable. Second, we did the analysis at the Zip Code level. Both these variants resulted in quantitatively similar results.

²⁴There are many, perhaps more first-order, reasons for corporate ownership of establishments, and this is extensively studied, e.g. Lafontaine and Shaw (2005), Kosová, Lafontaine, and Perrigot (2013), and Nishida and Yang (2018).

incomes have fewer establishments, suggesting that the quick-service restaurants we consider are inferior goods. Consistent with monitoring costs, we find that chains open fewer establishments in counties that are further away from their headquarters. The coefficient on the access to capital ranking is negative, implying that states with better access to capital have more establishments. We posit that the access to capital ranking proxies for the quantity and quality of the local entrepreneur base, providing a possible explanation for this result. Finally, the size of the county (in terms of area) is not significant and, interestingly, counties with higher wages have more establishments.

4.2 Structural Model

Our primary goal is to quantify the impact of the termination regulations on market structure. We do so in this section by specifying and estimating a structural model of chain-level entry decisions. Although we control for competition in the previous exercise, the regression analysis is not well suited for predicting counterfactual outcomes because we cannot easily solve for the equilibrium under an alternative regulation status using the IV strategy regression framework. Therefore, we propose and estimate a simple model of chain entry decisions at the county-level that allows us to make such predictions. The cost of this is making some additional assumptions, which we discuss below.

We closely follow the modeling strategy of Bresnahan and Reiss (1991) (hereafter, BR91). A key difference is that in our setting a chain decides the number of establishments, whereas in BR91 each establishment makes a single entry decision and there are no chain effects. We model the payoff to chain j of opening N establishments in county m as a function of the observable county/chain characteristics, X_{jm} , the number of rival establishments ($N_{-j,m}$) in the county, and the number of own-chain establishments ($N_{j,m}$). Formally, we specify the payoff as a linear function of these components:

$$u(N_{j,m}, N_{-j,m}; X_{jm}) = X_{jm}\beta + \Delta^o(N_{j,m} - 1) + \Delta^r(N_{-j,m}) + \epsilon_{jm}, \quad (5)$$

Importantly, the vector X_{jm} contains a variable indicating whether or not county m is located in a regulated state. We can connect this empirical approach directly to the model presented in Section 2 by noting that this payoff function represents the profit functions in Equations 1 and 2, where the regulation status in X_{jm} determines which of these two profit functions are relevant. Specifically, the regulation represents a fixed cost of entry for the franchisor.²⁵ Note that the empirical model also includes the impact of rival-chain competition, something

²⁵We thank one of the referees for pushing us to estimate the BR91 model and connecting it to the model in Section 2.

which we abstracted away from in Section 2.

In order to solve for the equilibrium of this model, we make the following assumptions that are common to the entry literature: (Assumption 1) ϵ is i.i.d. normally distributed; (Assumption 2) each chain knows the full payoffs of all other chains; (Assumption 3) chains play a simultaneous Nash equilibrium in the choice of the number of establishments to open. In our context, we only observe a single cross-section of the equilibrium outcomes (as of 2012), meaning assumption (c) implies that these outcomes are a result of a single static equilibrium of franchisor decisions. While it is clear that not all entry happens simultaneously, there is a long literature employing this modeling strategy in order to reduce complex dynamic games to static games in order to understand the determinants of entry decisions; see, for example, Berry (1992), Seim (2006), and Ciliberto and Tamer (2009), among many others.

Under these assumptions, an equilibrium occurs when each chain maximizes their total payoff in a county, $N_{j,m} \times u_{jm}$, by best responding to their rivals' strategies, which can be summarize by the following two conditions:

$$u(N_{j,m}; N_{-j,m}) \geq 0 \text{ and } u_{im}(N_{j,m} + 1; N_{-j,m}) \leq 0.$$

There are two complications in solving and estimating this model. First, since BR91, it is well known that these class of simultaneous entry games have multiple equilibria. Second, our setting is more complicated than that of the classic entry literature in that we model the chain as potentially choosing multiple establishments.²⁶ Therefore, in order to estimate the model, we make the following two additional assumptions:

Assumption 4: $\Delta(N_m) = \Delta^o(N_{j,m} - 1) + \Delta^r(N_{-j,m}); N_m = N_{j,m} - 1 + N_{-j,m}$

Assumption 5: $X_{jm} = X_m$

Assumption 4 implies that the competition from rival chains is symmetric, both in the sense that the effect of across-chain competition is the same as within-chain competition and that the effect is the same for every chain (i.e. Δ^w and Δ^a are not indexed by j). This can be justified by the fact that franchisees/managers under the same brand name compete with each other in a single market, implying that the demand-side implications of competition are independent of the brand of the rivals. The threats to this assumption would be if demand substitution differed based on geographic factors or brand preference, or

²⁶Ellickson, Houghton, and Timmins (2013) use a median inequalities to estimate a multi-unit chain entry game with a richer payoff specification, but their game of big-box retailers only has a small number of outcomes, whereas the number of establishments in our setting is much larger, making their approach difficult to implement. Additionally, Aradillas-López and Gandhi (2016) provide a method for estimating chain-level entry games.

if there were nonlinear costs in the number of establishments from the franchisors point of view. Assumption 5 implies that only variables that are common across all establishments in a county enter establishment level-payoffs. Therefore, the payoffs are symmetric across establishments in a county up to the random shock ϵ . The main cost of this is that we are not able to include any chain-level shifters of profits, or make chain-specific predictions about the effects of the regulation.

Under these two assumptions, the equilibrium of the game is unique in the *number of total establishments*, N_m , due to the monotonicity of the payoff function, even though there are multiple equilibria in the *identity* of the entrants. We note that, while BR91 show uniqueness in the equilibrium for a single-establishment game (i.e., no chains), the logic extends directly to our game with multi-unit chains under assumptions (4) and (5). A nice result that is demonstrated by BR91 is that when outcomes are aggregated to the market level, this model is equivalent to an ordered probit where the dependent variable is the total number of establishments in a county and there are outcome-specific cutoffs. Therefore, in order to determine the parameters of payoff function, we estimate the following ordered probit model:

$$Pr(N_m = N_m^*) = Pr(\pi_{N_m^*} < u(N_m; X_m) \leq \pi_{N_{m+1}^*}) \quad (6)$$

The terms denoted $\pi_{N_m^*}$ represent the outcome specific constants in the ordered probit, which are the level of per-establishment profit needed to support N_m establishments in the county (i.e., profit cutoffs). Note that $\pi_0^* = -\infty$ and $\pi_{N^{max}+1}^* = -\infty$, where N^{max} is the maximum outcome observed in the data.

Similar to BR91, we focus on isolated markets by restricting our sample to only counties with less than 50,000 in population in 2012, a set that we denote M . This totals 2,136 of the approximately 3,100 counties in the US. Summary statistics for the restricted sample are presented in Table 4. The top panel presents the outcomes in terms of total establishments per county across all five chains. The average county in this sample has 2.05 total establishments and 2 franchises per 10,000 people, and regulated counties have about 3.5% (3%) fewer establishments (franchises) per capita. Note that $N^{max} = 20$ and we do not observe the outcome $N^m = 18$ in the data.

Included in X_m , besides the regulation variable, are the same county-level characteristics that we included in regressions, with the exception of the distance to HQ variable. This variable is specific to each chain, so Assumption (5) implies we cannot include it. Instead, we allow for the average distance to HQ across all five chains to impact the payoff of each chain. The bottom panel shows the summary statistics for these variables in the restricted sample. The average population in these counties is about 18,000, while the average income, size (in land area), and wages are slightly smaller than the average across all counties in the

US. Finally, not surprisingly, significantly fewer of these counties have an interstate highway.

Table 4: Summary Statistics, Restricted Sample

Variable	Mean	Q25	Median	Q75
<i>Outcomes</i>				
Franchises	3.80	1.00	3.00	6.00
Total	3.91	1.00	3.00	6.00
Franchises per capita (10k)	2.00	1.16	1.86	2.50
Total per capita (10k)	2.05	1.20	1.91	2.55
<i>Unregulated States</i>				
Franchises per capita (10k)	2.02	1.04	1.79	2.48
Total per capita (10k)	2.07	1.05	1.86	2.54
<i>Regulated States</i>				
Franchises per capita (10k)	1.96	1.35	1.96	2.52
Total per capita (10k)	2.00	1.41	2.00	2.57
<i>Controls</i>				
Regulation	0.33	–	–	–
Dist to HQ	1,069	592	956	1,454
Population	18,482	7,697	15,607	27,327
Mean HH Income	52,015	45,481	50,810	56,841
Area, Sq. Miles	10,005	2,030	3,696	6,648
Mean Wage	13,299	10,508	11,821	13,391
Interstate Highway	0.30	–	–	–

Notes: The unit of observation for all rows is a county. There are about 3,100 county observations. Source: US Census Bureau, Company 10Ks and FDDs, and AggData.

We now turn to the estimates of the ordered probit model in Table 5. There are a few things to note. First, the sign and significance of the non-regulation control variables are similar to the regression analysis, except for wages, which are no longer significant, and land area, which is now significant and negative. Second, the coefficient on the regulation dummy variable is negative and significant, suggesting that the regulations impact entry decisions. While the magnitude of the coefficient cannot be directly interpreted, we use the coefficient on population to give it some context. Specifically, using the coefficient on (log) population, we calculate that the impact of the regulation in the median county, with a population of 15,607, is equivalent to reducing the local population by $18,482 \times \frac{-0.12}{2.312} \approx 959$ people, or about 5%.²⁷ Using data from McDonalds' 2019 financial statement, a ballpark figure for the impact of the regulation on profit of each establishment is about \$5,700 annually.²⁸ Third,

²⁷The marginal impact of one person is $2.312 \times \frac{1}{18,482}$ due to the log-linear form.

²⁸We calculate net income for McDonalds in the US by multiplying the total net income (\$6.025B) by the share of total revenue that is earned in the US versus internationally (0.372). We then divide by the total US population (382M) to get that McDonalds earns about \$5.90 per person in the US.

the difference in the estimated π_1 and π_2 is about 19%, suggesting a large jump in potential profit ($18,482 \times \frac{1.393}{2.312} \approx 11,000$ in population) is needed for a monopoly market to become a duopoly. This difference shrinks to about 5% ($18,482 \times \frac{0.512}{2.312} \approx 4,000$ in population) going from four to five establishments and is relatively level thereafter. This concavity in thresholds is qualitatively similar to BR91.

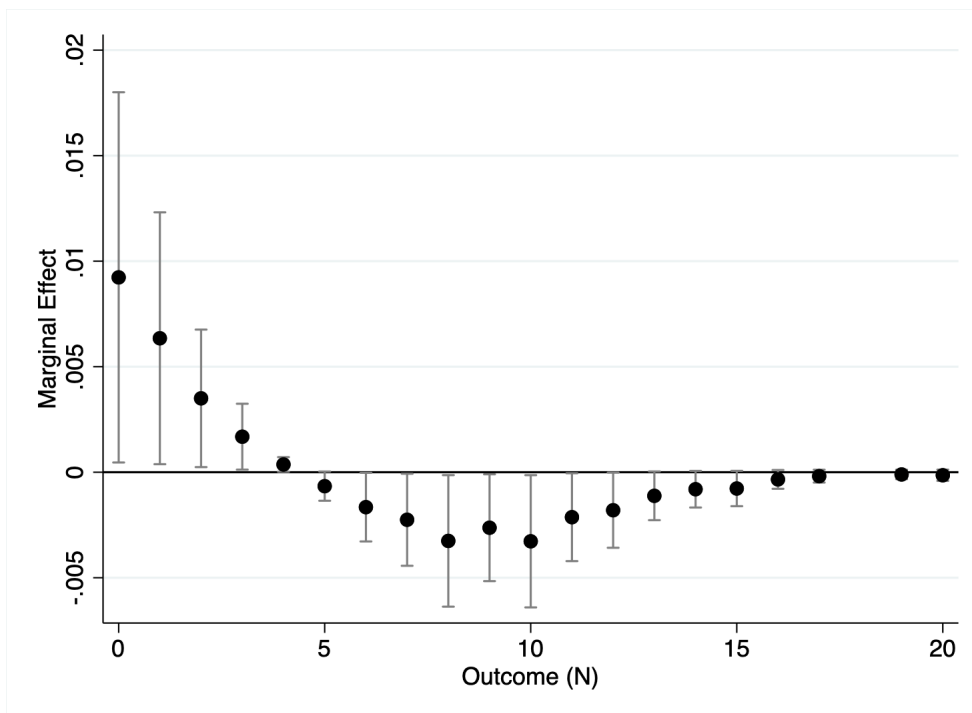
Table 5: Estimates of Ordered Probit

Variable	Estimate	Variable	Estimate	Variable	Estimate
Regulation	-0.12 (0.058)	π_1	7.415 (1.506)	π_{10}	12.952 (1.517)
Log(Pop)	2.312 (0.055)	π_2	8.808 (1.506)	π_{11}	13.356 (1.518)
Log(Income)	-0.868 (0.107)	π_3	9.709 (1.508)	π_{12}	13.657 (1.518)
Log(Area)	-0.097 (0.029)	π_4	10.399 (1.51)	π_{13}	13.97 (1.518)
Log(Wage)	0.006 (0.083)	π_5	10.911 (1.512)	π_{14}	14.224 (1.519)
Access to Capital Rank	-0.01 (0.002)	π_6	11.394 (1.513)	π_{15}	14.469 (1.52)
Log(HQ Dist)	-0.364 (0.116)	π_7	11.833 (1.515)	π_{16}	14.825 (1.523)
Interstate	0.566 (0.052)	π_8	12.212 (1.516)	π_{17}	15.09 (1.527)
		π_9	12.638 (1.516)	π_{18}	15.325 (1.535)
				π_{19}	15.541 (1.549)
Pseudo R-Sq	0.304	N	2,136		

Notes: Standard errors in parentheses. Outcome $N = 18$ is not observed in the data, meaning that π_{18} is the cutoff for $N = 19$ and π_{19} is the cutoff for $N = 20$

To further analyze the impact of the regulations, we present the marginal effects the regulation dummy on the probability of each outcome in Figure 2. The figure indicates that the probability of a county having fewer than five establishments increases, while the probability of outcomes with five or more decreases. These effects are statistically significant from zero up to $N_m = 12$. Overall, the estimated marginal effects imply that the probability of having fewer than five establishments in a county increases by slightly more than 2% due to the regulation.

Figure 2: Marginal Effects of the Regulation



Notes: The dots are the point estimates of the marginal effects on each outcome and the confidence bands indicate the 95% confidence region.

4.3 Counterfactual: Market Structure with and without Franchise Regulation

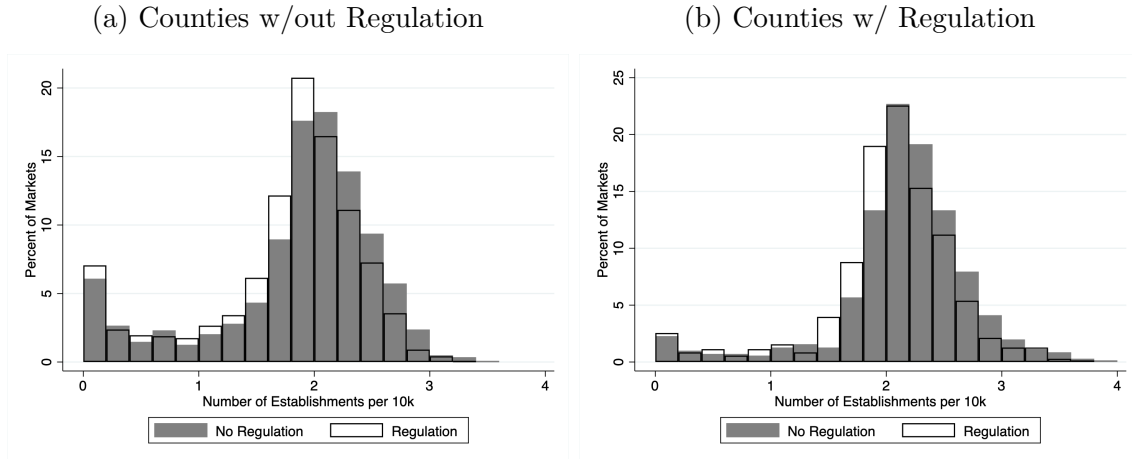
We use the estimated ordered probit model to perform two counterfactual exercises that focus on the impact of the contract termination regulations on local market structure. First, we quantify the effect of enacting the termination regulation in counties that currently do not have such laws, a set denoted M_1 . Therefore, this exercise can serve as an analysis of a federal statute, which is something that has been discussed by lobbyists and policy-makers. Second, we quantify the effect of removing regulations in counties that currently have them, a set denoted M_2 , thus measuring the equilibrium impact that current regulations have.

To perform these exercises, we use the model to calculate the expected number of establishments in each county under different regulation statuses (s), which we denote \tilde{N}_m^s . The status indicator can be either $s = 0$ (not regulated) or $s = 1$ (regulated). We do so with the following equation:

$$\tilde{N}_m^s = \sum_{n=0}^{20} \hat{P}_m^s(n) \times n \quad (7)$$

where $\hat{P}_m^s(n)$ is the model predicted probability of outcome n in county m under regulation

Figure 3: Impact of Changing Regulation Status



Notes: Histograms are based on the expected number of establishments (see equation 7) and are binned with a width of 0.2.

status s . We make these predictions by setting the regulation dummy to either 1 or 0, depending on the value of s . In order to focus on the impact on market structure, we believe it is important to control for population differences. We therefore examine all scenarios in terms of number of establishments per 10,000 residents of the county.

Figure 3 presents the distributions of the expected establishments per capita (10k) across the different scenarios. Figure 3a focuses on counties in M_1 , so the gray histogram represents the distribution of outcomes under the observed regulation status (i.e., \tilde{N}_m^0), or the baseline, and the white histogram represents the distribution of outcomes if these same counties enacted regulations laws, (i.e., \tilde{N}_m^1). It is clear that the distribution shifts to left (i.e., less competition) after the regulation is introduced. Indeed, using a Kolmogorov-Smirnov test, we find that the distribution of outcomes without regulation is significantly higher than the distribution with regulation (p-val < 0.001). Figure 3b focuses on the counties in M_2 , meaning the baseline distribution is in white, while the counterfactual distribution is in gray. Again, we see a shift to the left due to the regulation, which is statistically significant (KS test p-val < 0.001).

To get a better sense of how these changes impact market structure, we present different moments from these distributions in Table 6. The left panel focuses on counties in M_1 . The bottom row shows that average number of establishments per 10,000 residents falls from 2.08 to 1.98 in these counties due to the regulation, a reduction of about 4.8%, an effect that is statistically significant at the 5% level (SE of 0.05).²⁹ We further break down these distributions into three categories based on the market structure. The low competition

²⁹Standard errors for all outcomes in Table 6 are calculated based on 10,000 bootstrap samples.

markets are ones that have the number of establishments per capita (10k) below the 25th percentile of the baseline distribution (1.20 from Table 4), while the high competition markets are ones with the number of establishments per capita (10k) above the 75th percentile of the baseline (2.55 from Table 4). The medium competition markets are ones that are in-between these two thresholds. Individual cells in the table present the number of markets that fall into each category under the regulation status noted at the top. The number in parenthesis represents the standard error of the change between the baseline and the counterfactual, calculated using 10,000 bootstrap samples.

For M_1 markets, enacting the regulation results in the number of low competition markets increasing from 226 to 252 (11%), the number of medium competition markets increasing from 1,046 to 1,089 (4%), and the number of high competition markets decreasing from 171 to 102 (40%). The results are similar when focusing on M_2 in the right panel. Specifically, removing the regulation from M_2 counties results in the the average establishments per capita increasing by 0.1 (4.6%), the number of low competition markets decreasing by 15%, the number of medium competition markets decreasing by 7%, and the number of high competition markets increasing by 53%.

Table 6: Impact of the Regulation on the Distribution of N_m

Outcome	Sample: M_1		Sample: M_2	
	Baseline	CF	CF	Baseline
	Reg=0	Reg=1	Reg=0	Reg=1
# Markets w/ Low Competition (SE for Δ)	226 (13.18)	252	46 (4.53)	54
# Markets w/ Medium Competition (SE for Δ)	1046 (21.95)	1089	521 (20.37)	562
# Markets w/ High Competition (SE for Δ)	171 (30.84)	102	141 (22.8)	92
N per 10k (SE for Δ)	2.08 (0.05)	1.98	2.26 (0.05)	2.16

Notes: Low (high) competition is defined as the below (above) the 25th (75th) percentile of establishments per capita in the baseline. Medium competition is in the middle 50% of outcomes in the baseline. Standard errors calculated based on 10,000 bootstrap samples are in parentheses. In the top panel, these are standard errors of the difference between the baseline and the counterfactual.

Overall, the results of the counterfactuals imply that the regulations result in significantly more (less) markets that feature a low (high) levels of competition, thereby giving incumbent entrants more market power. While our data do not allow us to directly measure the welfare effects, these changes in market structure could result in higher prices faced by consumers. There could also be quality effects attributed to changes in local concentration. Further,

the reduction in establishments means a reduction in product variety, in terms of geographic differentiation, which is an additional cost to consumers.

5 Conclusion

We estimate the impact of state franchise contract termination regulations on market structure in the quick-service restaurant industry. The results of the analysis suggest that the regulations lead to a 4.8% (4.6%) reduction in the number of establishments per capita in the average unregulated (regulated) county. Further, the number of markets with a low level of competition increases by between 11% and 15%, while the markets with a high level of competition decreases by between 40% and 53% due to the regulations.

The importance of our analysis lies in the fact that we estimate the extent to which the regulations impact market structure. The relevance of this is further enhanced by the fact that these types of regulations have recently been proposed by more states and at the federal level. While lobbying groups for franchisees often argue that the regulations help protect franchisees from unfair treatment by franchisors, we show that the regulations also benefit the franchisees by limiting the amount of competition each franchisee faces. Therefore, we provide evidence that the regulations may represent a form of regulatory capture, something which has been of interest to the regulatory agencies in the federal government. One shortcoming of our analysis is that we are not able to estimate other effects of these regulations. For example, the regulations that we study may encourage higher quality entrepreneurs to become franchisees of national chains. This is clear and important direction for future research in this area.

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