Franchise Contract Regulations and Local Market Structure

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Abstract

Many US states have regulations 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 franchise regulations results in 4–5 percent fewer establishments in the average county. Our results imply that 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 12 percent and 15 percent with regulation.

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 (such as for hairdressers and medical professionals) and antitrust exemptions for hospital systems, the insurance industry, educational institutions, alcohol retailers, car dealerships, and gas stations. The US Department of Justice and Federal Trade Commission have recently focused on the potential anticompetitive effects of certain state regulations and the worry that they represent regulatory capture by businesses.[1]

In this paper, using the quick-service restaurant as a case study, we examine

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[1] This includes focus by the US Federal Trade Commission on occupational licenses and attention by the Department of Justice on state antitrust issues. For example, in 2018 the Department of Justice hosted a series of roundtables on the relationship between regulation and competition. In addition, Federal Trade Commissioner Joshua Wright discussed the importance of considering regulatory capture in high-tech industries in a speech in 2015 (see Wright 2015). State occupational licensing was successfully challenged in *North Carolina State Board of Dental Examiners v. FTC* (135 S. Ct. 1101 [2015]). This is a difficult area for federal competition authorities because generally state

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the competitive effects of common state regulations in franchised industries that restrict 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 that 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, which results in more concentrated markets.[2] Our contribution is to estimate the economic consequences of these franchise contract regulations, focusing on how they impact local market structure.

We begin by specifying a parsimonious 2-period model in which a franchisor chooses how many franchised establishments to open in a market. Each establishment is run by an entrepreneur who can be of either high or low quality, but the franchisor learns the entrepreneur's type after some time. In unregulated markets, the franchisor can replace an entrepreneur after his or her quality is revealed at the end of the first period. In regulated markets, the entrepreneur drawn in the first period operates the establishment for both periods. The model suggests that 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 indicate that the average chain has 9 percent fewer franchises and 8 percent fewer establishments (franchises plus corporate-owned stores) in regulated counties. Next, to make predictions about the impact of the regulations, we estimate a structural model of county-level entry that is based on Bresnahan and Reiss (1991) to account for the fact that observed entry patterns are the outcome of strategic interactions among competing chains. As in Bresnahan and Reiss's work, the model is estimated using an ordered probit model, where the outcome is the number of establishments in a county across the five chains. We further follow their work by analyzing small and medium-sized markets—counties with a population less than 50,000—which represent 2,150 of the 3,100 counties in our full sample.

The parameter estimates indicate that the regulations lead to more concentrated markets in equilibrium, as the likelihood that we observe the outcome of four or fewer establishments in a county is about 2 percent 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 do not have them (1,443) and

action is immune from antitrust liability according to the Parker immunity doctrine (see *Parker v. Brown,* 317 U.S. 341 [1943]).

[2] The franchise lobbying groups the Coalition of Franchisee Associations and the American Association of Franchisees and Dealers address franchise terminations in their bills of rights.

find that the number of establishments per capita would fall by about 4.8 percent in the average county. The number of markets with a low level of competition (in the bottom quartile of establishments per capita) increases from 226 to 252 (12 percent), while the number of markets with a high level of competition (in the top quartile of establishments per capita) decreases from 171 to 102 (40 percent). Second, we quantify the impact of removing restrictions in counties that currently have them (708). We find that the number of establishments per capita increases by 4.6 percent, the number of markets with a low level of competition decreases from 54 to 46 (15 percent), and the number of markets with a high level of competition increases from 92 to 141 (53 percent). Put together, the results suggest that the regulations significantly impact local market structure in this industry, which leads to more concentrated markets and a lower level of product variety available to consumers in terms of geographic differentiation.[3]

Our study is most closely related to other research examining the effects of franchise contract regulations on decisions about organizational form 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 regulations and show that the regulations have 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 that 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 that this cost results in fewer franchises. However, our analysis differs in that we examine how the regulations affect local market structure (the number of establishments) rather than focus on the substitution between franchisee- and company-owned establishments.[4] Therefore, for the primary analysis, we do not distinguish 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 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 in Brickley, Dark, and Weisbach (1991). While we rely on cross-sectional variation, our analysis differs

[3] Although we find that state franchise regulations are associated with fewer franchised establishments, the argument for the 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 regulations require higher up-front payments from franchisees.

[4] A rich literature focuses on the ownership structure of franchises outside the context of termination regulation. See, for example, Lafontaine and Shaw (2005), Kosová, Lafontaine, and Perrigot (2013), and Nishida and Yang (2018).

from Klick, Kobayashi, and Ribstein (2012) in a few important ways. First, our data are from more chains (five versus two) and include McDonald's 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, which accounts for heterogeneity in entry decisions in a state. Finally, we estimate a structural model of entry, which facilitates the 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 up-front investment requirements of franchisees. The results indicate that in states that implemented franchise regulations 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, 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 such as 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, other studies examine the effects of state regulations on competition and welfare. Blass and Carlton (2001) and Hastings (2004) examine contract divorcement 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 of the main results in Section 4. Finally, Section 5 concludes.

2. Model

> The [International Franchise Association] and others argue that equity protection for franchisees will hinder the franchisor's ability to expand strategically and could affect quality and consistency if

[5] Klick, Kobayashi, and Ribstein (2012) use 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 with which chains could contract around the regulations prior to the repeal.

> the company is not able to close underperforming stores or terminate franchisees who are not maintaining standards. (Daley 2015)

In this section, we develop a 2-period model of a chain's franchising decisions to motivate our empirical analysis. 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, which leads to the different outcomes 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 ex ante by the chain. During period 1, the revenue of each establishment is realized, and 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 particular establishment, and the ability to fire depends on whether contract termination restrictions are in place. Finally, during period 2, revenues of each establishment are again realized.

To simplify the exposition, we assume that the quality of each entrepreneur is either high ($\tau = \mathrm{h}$) or low ($\tau = \mathrm{l}$) 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: $\mathcal{M} = \{N^{\mathrm{h}}, N^{\mathrm{l}}\}$. We denote the per-period revenues from an establishment managed by a type τ entrepreneur $R^{\tau}_{\mathcal{M}}$, which is a function of 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 that 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 of firing 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

$$E[\pi^{\mathrm{U}}(N)] = \gamma \sum_{n=0}^{N} \underbrace{\Phi(N, n)}_{\Pr(\mathcal{M}=\{N-n,n\})} \left\{ \underbrace{[(N-n)R^{\mathrm{h}}_{(N-n,n)} + nR^{\mathrm{l}}_{(N-n,n)}]}_{\text{Period}-1 \text{ Revenues}} \right. \\ \left. + \underbrace{\sum_{r=0}^{n} \Phi(n, r)[(N-r)R^{\mathrm{h}}_{(N-r,r)} + rR^{\mathrm{l}}_{(N-r,r)}]}_{\text{Period}-2 \text{ Revenues}} \right\} - 2Nf, \tag{1}$$

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 of low quality. In the regulated (R) environment, the franchisor cannot fire the low-quality entrepreneur, so the expected value of choosing N establishments is

$$E[\pi^{\mathrm{R}}(N)] = 2\gamma\sum_{n=0}^{N}\Phi(N, n)[(N-n)R^{\mathrm{h}}_{(N-n,n)} + nR^{\mathrm{l}}_{(N-n,n)}] - 2Nf. \tag{2}$$

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

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

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

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

where $H(n; N)$ is the value of 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:

$$H(n;\ N) = R^{\mathrm{h}}_{(N-n+1,n)} + (N-n)R^{\mathrm{h}}_{(N-n+1,n)} - R^{\mathrm{h}}_{(N-n,n)} + n(R^{\mathrm{l}}_{(N-n+1,n)} - R^{\mathrm{l}}_{(N-n,n)}).$$

The first term of this expression is the revenue from the additional establishment, while the second and third terms 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

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

which means that the probability of adding a store before the realization of f is

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

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

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

The difference between this equation and the equation for the regulated environment is the second term in the square brackets, 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 who is of high quality with probability ϕ. The franchisor will choose to add an additional establishment in the unregulated environment as long as

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

which means that the probability of adding a store in the unregulated environment before the realization of f is

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

Taking the difference of equation (4) and equation (3) results in

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

which is positive under the assumption that the value of adding a high-quality establishment is always greater than adding a low-quality establishment.[6] Therefore, the probability of adding an additional store is higher in the unregulated environment than the regulated environment at all levels of N:

$$P^{\mathrm{U}}(N) > P^{\mathrm{R}}(N).$$

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 it is not modeled here, previous literature shows that there is substitution to company-owned establishments in regulated markets. However, as long as company-owned establishments are not perfect substitutes for franchises, this would only dampen the impact of the regulations on the total

[6] This might not be true if the competitive effects of adding high-quality establishments are large.

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.[7]

3. Data

Our empirical analysis focuses on the quick-service restaurant industry. Quick-service restaurant franchises (fast-food restaurants) constitute over 20 percent of the top 500 franchises according to industry sources (Herold 2014). It is estimated that these restaurants generated $570 billion in revenue 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 establishments that were open in 2012 for these five chains from data provided by a private firm, AggData.[8] These data feature addresses of all stores listed on each chain's website in late 2012 or early 2013. Table 1 reports the total counts of establishments by chain listed by AggData. Subway is the largest franchisor with over 26,000 establishments, followed by McDonald's 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 with the count provided by each chain in its 2012 annual report (see Table 1). Note that Subway is owned by a private company, so it does not produce an annual report. The AggData count is smaller than the count in the annual report 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 those reported in annual statements, as AggData collects its data 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 percent, which suggests that the AggData sample has good coverage.

We also collect the franchise status for each establishment, which indicates whether it is owned by a franchisee or the corporation. This information is not available from AggData, but a list of the addresses for the establishments that are franchised is reported in each chain's annual franchise disclosure document (FDD), which is the contract between the franchisor and franchisee. In many states, franchisors are required to report their FDDs to a government agency that, in turn, posts them online in portable document format. We collect the 2012

[7] 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.

[8] Klick, 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 provided us with only a single year of data. Second, we are not aware of recent changes in the regulations (Klick, Kobayashi, and Ribstein [2012] use changes from the 1990s). That our estimates in Table 3 are close to those in Klick, Kobayashi, and Ribstein (2012) is reassuring.

Table 1
Establishments by Chain

	Disclosure Documents: Franchises	AggData: All	Postmerge Sample		2012 Annual Reports	
			Franchises	All	Franchises	All
McDonald's	12,601	14,062	12,190	13,874	12,605	14,157
Burger King	6,895	6,981[a]	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		

Note. Burger King report does not separate Canadian from US establishments, so values include 293 stores in Canada. Subway is a privately owned company and does not publish financial information, including number of stores.
[a] From Burger King's franchise disclosure documents rather than AggData.

FDDs from the Minnesota Commerce Department's website.[9] The counts of franchises in the FDDs are displayed in Table 1. Not surprisingly, when we compare these figures with the data from the financial statements, we see that the patterns in the franchised establishments mirror those of total establishments.

To determine the status of each establishment, we merge the FDD data with the AggData sample as follows. We define the group of all establishments, both franchised and company owned, as the list of establishments provided by AggData. We define an establishment as franchised if it appears in both the information from AggData and the FDDs. To determine the intersection of the two lists, we merge them using multiple methods.[10] The matched sample is displayed in Table 1. In theory, every address in an FDD should also be on the list provided by AggData, but we do not get a 100 percent 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 likely for the FDDs read from hard copies by an optical scanner.

Finally, a comparison of our final (postmerge) sample with the information from the financial statements suggests some differences between our sample and the reported numbers, but they are not large in magnitude. However, one might worry that they are due to mistakes in our raw data and/or problems with merging the two data sources. The fact that these patterns also exist when comparing the premerged 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.

[9] See Minnesota Commerce Department, CARDS (https://www.cards.commerce.state.mn.us/CARDS/).

[10] First, we match common variables in the lists such as store phone number, zip code, and address. Second, we geocode each address using MapQuest and the Google Maps application programming interface and merge on latitude and longitude (at different levels of precision). Finally, we hand check the addresses that did not match and manually match them to provide the most complete coverage possible.

Overall, the information gathered suggests that franchisees own a majority, if not all, of the establishments for any particular chain. The smallest share of franchised establishments is about 78 percent (Wendy's), while the largest is 100 percent (Subway). McDonald's franchises comprise almost 90 percent of its establishments. The high propensity to franchise, which can be due to a number of reasons, implies that the termination laws are likely an important factor in determining the profitability of a chain.

3.1. Franchise Contract Regulations

States started to enact franchise termination regulations in the early 1970s following concerns about opportunism by franchisors (Klick, Kobayashi, and Ribstein 2009). Franchisees (and regulators) worried that if franchisors were able to easily terminate contracts, they would use franchising as a tool to learn about and take over the most profitable locations. Nicastro (1993) discusses this issue in the context of *Kealey Pharmacy v. Walgreen Co.* (607 F. Supp. 155 [W.D. Wis. 1984]). 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 franchisors will claim that "good cause" comes in the form of a breach of the franchise agreement by failing to make payments, failing inspections, or putting the trademark in jeopardy, among other reasons. However, the term "good cause" is typically left without a specific definition in many regulations, and its meaning is a primary point of argument in franchise litigation.[11] Nicastro (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 he or she feels that the contract was wrongfully terminated. In practice, the good-cause language makes defending the termination more difficult for the franchisor. Thus, 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. 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 and the Coalition of Franchisee Associations, which cite the need to protect franchises from large franchise corporations (Taylor 2014).

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 mentioned the termination statutes as an important issue that comes up in the defense of such claims during a presentation at the 2019 International Franchise Association Legal Symposium (Howard and Mair 2019).

[11] For example, a 7-Eleven franchisee in New Jersey recently lost a case in which he claimed that his contract termination was without good cause (see *7-Eleven, Inc. v. Sodhi,* No. 16-3163 [3d Cir., August 24, 2017]).

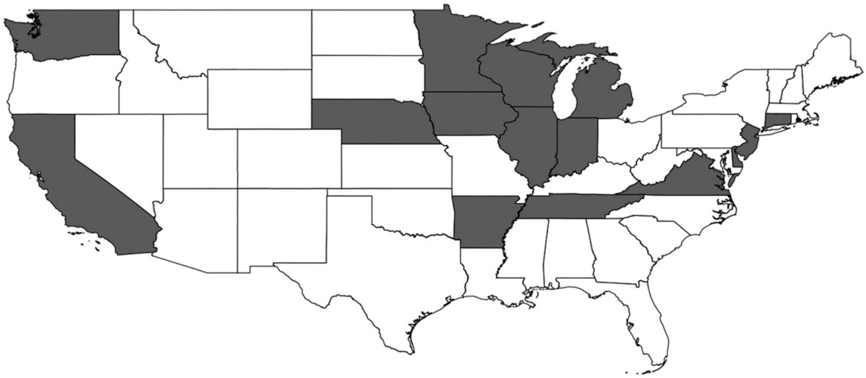

Figure 1. States with good-cause provisions

We collect the regulatory status of each state from Klick, Kobayashi, and Ribstein (2009).[12] 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 additional provisions such as a good-cause provision for nonrenewal 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, and we focus on it 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, for example, the Fair Franchise Act of 2017 introduced by Representative Keith Ellison of Minnesota.

In Figure 1, we show states (in gray) that have a 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. Alaska and Hawaii (not shown) do not have good-cause regulation.

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 population and the median income for all counties in the United States in 2012 using publicly available data from the US Census Bureau. We merge this information 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 Kosová and Sertsios (2018), we proxy for franchisors' monitoring costs using the distance from the establishment to the chain's headquarters. To determine this, we collect the location of each chain's headquarters from the

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

chain's website and calculate the driving distance from that location to each establishment using the MapQuest application programming interface. Third, to control for the importance of repeat customers, we collect information from the County Business Patterns data set on whether the county has an interstate highway passing through it. 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.[13] The idea is that the pool of local entrepreneurs, both in quantity and in quality, might be impacted by how easy it is to obtain the capital requirements to open a franchise.[14]

3.3. *Descriptive Statistics*

Table 2 presents descriptive statistics for our full sample. It shows the chain-level average establishment counts across counties, both in absolute and per capita terms, and the per capita averages by regulation status. There are an average of 3.8 total establishments and 3.6 franchised establishments per chain per county, which implies that about 93 percent of establishments are franchised in the average county. When controlling for population, the franchised share per capita is reduced to 90 percent, which suggests 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 of establishments and the number of franchises per capita are lower in regulated states.

Table 2 also shows 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 termination restrictions, which suggests that the regulations are not concentrated in states with a relatively large or small number of counties (16/50 states = .32). Many of the restaurants are far from the franchisor's headquarters: the average distance is almost 1,000 miles, about the same distance as a drive from Boston to Chicago. The median annual wage for a worker in the industry is quite low at $12,600, and fewer than half the counties in the United States have an interstate running through them.

4. Analysis

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 of 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 to predict

[13] See CNBC, America's Top States for Business 2012 (https://web.archive.org/web/20130125231447/http://www.cnbc.com/id/100016697).

[14] To open a franchise, the franchisee typically needs to pay substantial start-up 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.

Table 2

Summary Statistics: Full Sample

	Mean	25th Quartile	Median	75th Quartile
Outcomes:				
Franchises	3.57	0	1.00	3.00
All establishments	3.83	0	1.00	3.00
Franchises per capita	.40	0	.24	.57
All establishments per capita	.42	0	.26	.59
Unregulated states:				
Franchises per capita	.41	0	.23	.55
All establishments per capita	.42	0	.25	.57
Regulated states:				
Franchises per capita	.39	0	.26	.60
All establishments per capita	.41	0	.28	.61
Controls:				
Regulation	.33			
Distance 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
Land Area (square miles)	15,132	2,440	4,672	9,927
Mean Wage	13,634	11,071	12,601	14,325
Interstate Highway	.44			

Note. The unit of observation for outcomes is a chain-county ($N = {\sim}3{,}100$). The unit of observation for the controls is a county ($N = {\sim}15{,}500$). Per capita values are per 10,000 people.

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 and county and chain characteristics.[15] 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's headquarters. We also include a statewide measure of entrepreneurial access to capital (ranked 1–51), a dummy variable indicating whether an interstate highway passes through the county, a fixed effect for each census region, and a fixed effect for each chain.

Before discussing the county-level results, we point to the state-level results in Table 3, which provide a comparison to the analysis of Klick, Kobayashi, and

[15] We adjust the dependent variable by 1 to account for the zeros. We estimate the regressions using an arctangent approximation with similar results.

Table 3

Impact of Regulations on the Number of Establishments, 2012

	County Level ($N = 15{,}415$)				State Level ($N = 250$)	
	Log Franchises		Log All Establishments		Log Franchises	Log All Establishments
	(1)	(2)	(3)	(4)	(5)	(6)
Regulation	−.059	−.091	−.062	−.081	−.083	−.050
	(.013)	(.032)	(.014)	(.026)	(.057)	(.055)
Rivals		−.885		−.520		
		(.551)		(.451)		
Log Population	.481	1.187	.508	.922	1.016	1.016
	(.009)	(.444)	(.009)	(.363)	(.032)	(.032)
Log Median Income	−.279	−.700	−.283	−.530	−.322	−.398
	(.072)	(.317)	(.078)	(.258)	(.109)	(.108)
Log Land Area (square miles)	.019	.007	.013	.007	−.050	−.037
	(.007)	(.015)	(.007)	(.013)	(.020)	(.019)
Log Wage	.257	.443	.276	.385	−.652	−.555
	(.028)	(.132)	(.030)	(.107)	(.116)	(.115)
Access to Capital	−.003	−.006	−.003	−.004	.002	−.000
	(.001)	(.002)	(.001)	(.002)	(.002)	(.002)
Log HQ Distance	−.073	−.071	−.068	−.067	−.249	−.225
	(.010)	(.019)	(.010)	(.015)	(.096)	(.100)
Interstate Highway	.156	.372	.171	.298	.083	.075
	(.014)	(.137)	(.015)	(.112)	(.057)	(.056)
Constant	−3.396	−6.241	−3.835	−5.505	1.217	.932
	(.702)	(2.366)	(.758)	(1.925)	(.887)	(.917)
R^2	.778	.487	.801	.665	.637	.651

Note. The dependent variable is log establishments (plus adjustment). All regressions include census region effects and chain effects. Robust standard errors are in parentheses and are clustered at the county level for county-level results.

Ribstein (2012).[16] Recall that Klick, Kobayashi, and Ribstein (2012) use panel data to identify the effect of within-state changes in the regulation status, while we rely on cross-sectional variation. The dependent variables in our regressions are the (logged) numbers of franchises (five) and establishments (six) for a chain in a state. We find that there are 8.3 percent fewer franchises and 5 percent fewer establishments for a chain in regulated states. These are comparable to the estimates in Klick, Kobayashi, and Ribstein (2012, table 2), as they find that changes in law in Iowa and Washington, DC, resulted in 8 percent fewer franchised units for Burger King. However, our estimates are not significant at the 5 percent level.

For the county-level regressions, standard errors are clustered at the county level. An advantage of this approach is that we are able to control for within-state heterogeneity in observable characteristics and the impact of local competition. Four specifications in Table 3 differ in their dependent variable and control for competition from other chains. First, focusing on the results of specifications (1) and (3), which ignore the impact of competition, the regulations result in about 5.9 percent fewer franchises and 6.2 percent 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 the estimate. That is, if the regulation implies fewer establishments, then it may be attractive for chains to enter regulated markets to avoid competition. This suggests that the effects of specifications (1) and (3) are biased toward 0. The state-level estimates in Table 3 are also likely biased.

Therefore, to capture the impact of competition, we estimate specifications in which we include the total number of rival quick-service establishments (logged) from the other four chains as a regressor. As is common in this type of analysis, there is an endogeneity problem: the number of rival establishments is likely correlated with the error in the regression. For example, if a county is attractive to a particular chain for unobservable reasons, then it is probably also attractive to rivals for the same reasons. To address this issue, we instrument for the number of rivals using Distance from HQ logged for the rival with the shortest distance. Our assumptions for the validity of this instrument are that the distance for rivals does not directly affect the chain's payoff from entering, and the shortest distance among rivals is a strong predictor of the number of rivals. The results of the first-stage regression indicate that the impact of the closest rival's distance to headquarters is negative and significant at the 1 percent level: the number of rivals decreases by 3.6 percent for a 1 percent increase in distance (the coefficient is .036, and the standard error is .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. Impor-

[16] State-level population is the sum of the population of all counties in a state, while the other controls are the population-weighted averages across counties in a state. The exception is Interstate Highway, which indicates the number of counties in the state with at least one interstate running through the county.

tantly, 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 percent lower and the number of establishments per chain is about 8.1 percent lower in counties that are regulated, and these effects are significant at the 5 percent level, which suggests that regulated counties are more concentrated.[17] Furthermore, the fact that the change in the number of establishments is less than the change in the number of franchises implies there is a substitution effect between franchisee and company-owned establishments, which is examined in Brickley, Dark, and Weisbach (1991), among other studies. The difference means that some of the reduction in franchises is made up for by the chain opening its own establishments, although the difference between the coefficients is not statistically significant.[18]

The results also indicate that counties with a larger population and those with an interstate highway, which are proxies for demand, have more establishments. Counties with higher incomes have fewer establishments, which suggests 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 farther from their headquarters. The coefficient on the ranking for access to capital is negative, which implies that states with better access to capital have more establishments. We posit that the ranking proxies for the quantity and quality of the local entrepreneur base, which provides a possible explanation for this result. Finally, the size of the county (in square miles) 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 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 instrumental-variables regression framework. Therefore, we propose and estimate a simple model of chains' entry decisions at the county level that allows us to make such predictions. The cost of this is making some additional assumptions.

We closely follow the modeling strategy of Bresnahan and Reiss (1991). A key difference is that in our setting a chain decides the number of establishments, whereas in Bresnahan and Reiss (1991) each establishment makes a single en-

[17] We ran two variations of these regressions. First, we estimated Poisson regressions, with the count of establishments being the dependent variable. Second, we did the analysis at the zip-code level. The variations resulted in quantitatively similar results.

[18] There are many reasons, and perhaps more first-order reasons, for corporate ownership of establishments. This has been extensively studied; see for example, Lafontaine and Shaw (2005), Kosová, Lafontaine, and Perrigot (2013), and Nishida and Yang (2018).

try 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 and chain characteristics $\boldsymbol{X}_{jm}$, 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:

$$u(N_{j,m}, N_{-j,m}; \boldsymbol{X}_{jm}) = \boldsymbol{X}_{jm}\beta + \Delta^{o}(N_{j,m} - 1) + \Delta^{r}(N_{-j,m}) + \varepsilon_{jm}. \tag{5}$$

Importantly, the vector $\boldsymbol{X}_{jm}$ contains a variable indicating whether 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 $\boldsymbol{X}_{jm}$ determines which profit function is relevant. That is, the regulation represents a fixed cost of entry for the franchisor.[19] Note that the empirical model also includes the impact of competition from a rival chain, something we abstracted away from in Section 2.

To solve for the equilibrium of this model, we make the following assumptions that are common to the entry literature:

Assumption 1. The term ε is independently and identically 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 observe only a single cross section of the equilibrium outcomes (as of 2012), which mean that assumption 3 implies that these outcomes are a result of a single static equilibrium of franchisors' decisions. While it is clear that not all entry happens simultaneously, there is a long literature employing this modeling strategy to reduce complex dynamic games to static games so as to understand the determinants of entry decisions; see, for example, Berry (1992), Seim (2006), and Ciliberto and Tamer (2009).

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

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

There are two complications in solving and estimating this model. First, since Bresnahan and Reiss (1991), it is well known that these simultaneous-entry games have multiple equilibria. Second, our setting is more complicated than that in the classic entry literature because we model the chain as potentially choosing

[19] We thank a referee for pushing us to estimate the Bresnahan and Reiss (1991) model and connect it to the model in Section 2.

multiple establishments.[20] Therefore, to estimate the model, we make the following two additional assumptions:

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

Assumption 5. We assume $\boldsymbol{X}_{jm} = \boldsymbol{X}_m$.

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 (Δ^{w} and Δ^{a} are not indexed by j). This can be justified by the fact that franchisees and managers under the same brand name compete with each other in a single market, which implies that the demand-side implications of competition are independent of the rivals' brand. The threats to this assumption would be if demand substitution differed on the basis of geographic factors or brand preference or 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 establishments N_m because of the monotonicity of the payoff function, even though there are multiple equilibria in the identity of the entrants. While Bresnahan and Reiss (1991) show uniqueness in the equilibrium for a single-establishment game (no chains), the logic extends directly to our game with multiunit chains under assumptions 4 and 5. A nice result demonstrated by Bresnahan and Reiss (1991) is that when outcomes are aggregated to the market level, this model is equivalent to an ordered probit model in which the dependent variable is the number of establishments in a county, and there are outcome-specific cutoffs. Therefore, to determine the parameters of the payoff function, we estimate the following ordered probit model:

$$\Pr(N_m = N_m^\star) = \Pr(\pi_{N_m^\star} < u(N_m;\, \boldsymbol{X}_m) \leq \pi_{N_{m+1}^\star}). \tag{6}$$

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

Similar to Bresnahan and Reiss (1991), we focus on isolated markets by restricting our sample to counties with fewer than 50,000 residents in 2012, a set

[20] Ellickson, Houghton, and Timmins (2013) use median inequalities to estimate a multiunit chain entry game with a richer payoff specification, but their game of big-box retailers has only a small number of outcomes. The number of establishments in our setting is much larger, which makes their approach difficult to implement. In addition, Aradillas-López and Gandhi (2016) provide a method for estimating chain-level entry games.

Table 4

Summary Statistics: Restricted Sample

	Mean	25th Quantile	Median	75th Quantile
Outcomes:				
Franchises	3.80	1.00	3.00	6.00
All establishments	3.91	1.00	3.00	6.00
Franchises per capita	2.00	1.16	1.86	2.50
Total establishments per capita	2.05	1.20	1.91	2.55
Counties in unregulated states:				
Franchises per capita	2.02	1.04	1.79	2.48
Total establishments per capita	2.07	1.05	1.86	2.54
Counties in regulated states:				
Franchises per capita	1.96	1.35	1.96	2.52
Total establishments per capita	2.00	1.41	2.00	2.57
Controls:				
Regulation	.33			
Distance 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
Land Area (square miles)	10,005	2,030	3,696	6,648
Mean Wage	13,299	10,508	11,821	13,391
Interstate Highway	.30			

Note. The unit of observation for the controls is a county ($N = {\sim}3{,}100$). Per capita values are per 10,000 people.

that we denote M. This set includes 2,136 of the approximately 3,100 counties in the United States. Summary statistics for the restricted sample are presented in Table 4. The average county in the sample has 2.05 establishments and two franchises per 10,000 people, and counties in regulated states have about 3.5 percent (3 percent) fewer establishments (franchises) per capita than counties in unregulated states. Note that $N^{\text{Max}} = 20$, and we do not observe the outcome $N_m = 18$ in the data.

Included in $\boldsymbol{X}_m$, in addition to the regulation variable, are the same county-level characteristics that were in the regressions, with the exception of Distance to HQ, which is specific to each chain, so assumption 5 implies that we cannot include it. Instead, we allow for the average distance to headquarters across the five chains to impact the payoff of each chain. The average population in these counties is about 18,000, while the average income, size (in area), and wages are slightly smaller than the averages across all counties in the United States. Finally and not surprisingly, significantly fewer of these counties have an interstate highway.

For the estimates of the ordered probit model in Table 5, the sign and significance of the nonregulation control variables are similar to those in the regression analysis except for wages, which are no longer significant, and land area, which is significant and negative. The coefficient on Regulation is negative and significant, which suggests that the regulations impact entry decisions. While the magnitude of the coefficient cannot be directly interpreted, the coefficient on Population

Table 5
Estimates from the Ordered Probit Model

	Coefficient		Coefficient
Regulation	−.12	π_7	11.833
	(.058)		(1.515)
Log(Population)	2.312	π_8	12.212
	(.055)		(1.516)
Log(Mean HH Income)	−.868	π_9	12.638
	(.107)		(1.516)
Log(Land Area)	−.097	π_{10}	12.952
	(.029)		(1.517)
Log(Mean Wage)	.006	π_{11}	13.356
	(.083)		(1.518)
Access to Capital Rank	−.01	π_{12}	13.657
	(.002)		(1.518)
Log(Distance to HQ)	−.364	π_{13}	13.97
	(.116)		(1.518)
Interstate Highway	.566	π_{14}	14.224
	(.052)		(1.519)
π_1	7.415	π_{15}	14.469
	(1.506)		(1.52)
π_2	8.808	π_{16}	14.825
	(1.506)		(1.523)
π_3	9.709	π_{17}	15.09
	(1.508)		(1.527)
π_4	10.399	π_{18}	15.325
	(1.51)		(1.535)
π_5	10.911	π_{19}	15.541
	(1.512)		(1.549)
π_6	11.394		
	(1.513)		

Note. Standard errors are in parentheses. Outcome $N = 18$ is not observed in the data, which means that π_{18} is the cutoff for $N = 19$ and π_{19} is the cutoff for $N = 20$. Psuedo-$R^2 = .304$; $N = 2{,}136$.

gives it some context. 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 $18{,}482 \times (-.12/2.312) \approx 959$ people, or about 5 percent.[21] Using data from McDonald's 2019 financial statement, a ballpark figure for the impact of the regulation on the profit of each establishment is about \$5,700 annually.[22] The difference in the estimated values of π_1 and π_2 is about 19 percent, which suggests that a large jump in potential profit ($18{,}482 \times (1.393/2.312) \approx 11{,}000$ in population) is needed for a monopoly market to become a duopoly. This difference shrinks to about 5 percent ($18{,}482 \times (.512/2.312) \approx 4{,}000$ in population) with an increase from four to five establish-

[21] The marginal impact of one person is $2.312 \times (1/18{,}482)$ because of the log-linear form.

[22] We calculate net income for McDonald's in the United States by multiplying the total net income (\$6.025 billion) by the share of revenue earned in the United States versus internationally (.372). We then divide by the US population (382 million) to find that McDonald's earns about \$5.90 per person in the United States.

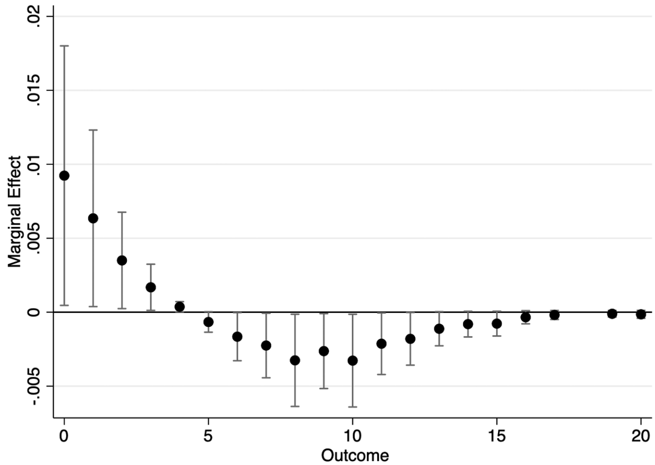

Figure 2. Marginal effects of regulations

ments and is relatively level thereafter. This concavity in thresholds is qualitatively similar to the results in Bresnahan and Reiss (1991).

To further analyze the impact of the regulations, we present the marginal effects of Regulation on the probability of each outcome in Figure 2 (with 95 percent confidence intervals). The probability of a county having fewer than five establishments increases, while the probability of outcomes with five or more establishments decreases. These effects are statistically significant from 0 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 percent because of a regulation.

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 a 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, and thus measure 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:

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

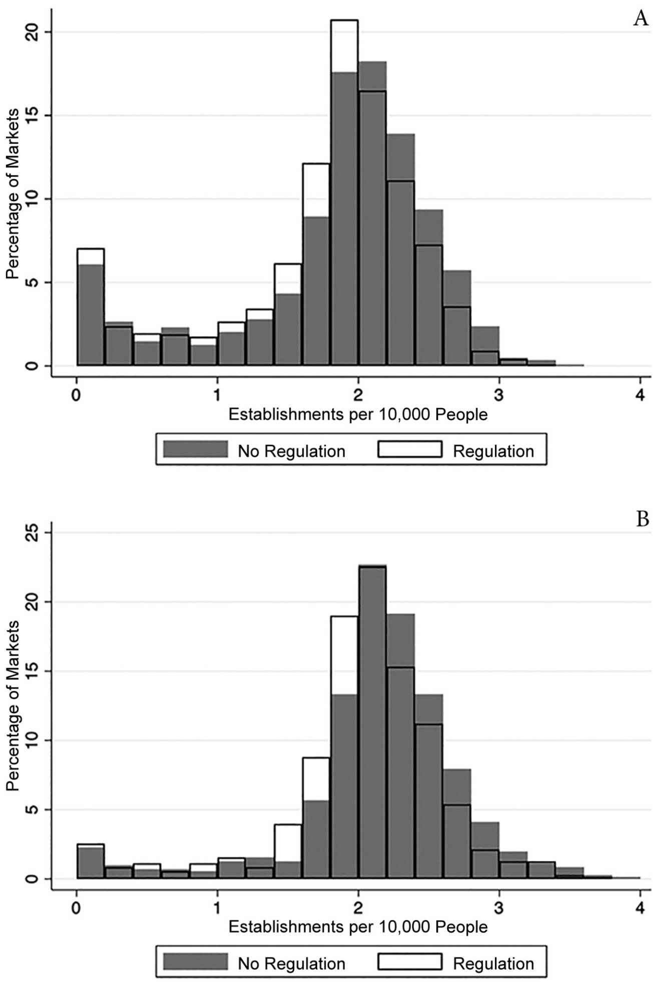

Figure 3. Impact of changing regulation status**.** *A,* Counties without regulation; *B,* counties with regulation.

where $\hat{P}^s_m(n)$ is the predicted probability of outcome n in county m under regulation status s. We make these predictions by setting Regulation to either one or zero, depending on the value of s. To focus on the impact on market structure, we believe that it is important to control for population differences. We therefore examine all scenarios in terms of the number of establishments per 10,000 residents of the county.

Figure 3 presents the distributions of the expected establishments per capita (10,000 people) across the scenarios. Figure 3*A* focuses on counties in M_1 and indicates the distribution of outcomes under the observed regulation status $(\tilde{N}^0_m)$ or the baseline and the outcomes if the same counties enacted regulations ($\tilde{N}_m^1$). It is clear that the distribution shifts to the left (less competition) after a regulation is introduced. Indeed, using a Kolmogorov-Smirnov test, we find that the distribution of outcomes without regulation is significantly higher than that with regulation ($p < .001$). Figure 3*B* focuses on the counties in M_2. Again we see a shift to the left as a result of the regulation, and it is statistically significant ($p < .001$, Kolmogorov-Smirnov test).

To get a better sense of how these changes impact market structure, we present different moments from these distributions in Table 6. For counties in M_1, the average number of establishments per 10,000 residents experiences a reduction of about 4.8 percent because of the regulations, an effect that is statistically significant at the 5 percent level. We break down these distributions into three categories based on the market structure. The low-competition markets have the number of establishments per capita (10,000 people) below the 25th percentile of the baseline distribution (1.20 from Table 4), while the high-competition markets have the number of establishments per capita (10,000 people) above the 75th percentile of the baseline (2.55 from Table 4). The medium-competition markets are between these thresholds. Table 6 presents the number of markets in each category.

For M_1 markets, enacting the regulation results in the number of low-competition markets increasing 12 percent, the number of medium-competition markets increasing 4 percent, and the number of high-competition markets decreasing 40 percent. The results are similar when focusing on M_2. Removing the regulations from M_2 counties results in the average establishment per capita increasing by 4.6 percent, the number of low-competition markets decreasing by 15 percent, the number of medium-competition markets decreasing by 7 percent, and the number of high-competition markets increasing by 53 percent.

Overall, the results of the counterfactuals imply that the regulations result in significantly more (fewer) markets that feature low (high) levels of competition, which gives 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 for consumers. There could also be quality effects attributed to changes in local concentration. Furthermore, 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 percent (4.6 percent) reduction in the number of establishments per capita in the average unregulated (regulated) county. Furthermore, the number of markets with a low level of competition increases by between 12 percent and 15 percent, while the number of markets with

Table 6

Impact of the Regulations on the Distribution of Establishments

	M_1			M_2		
	No Regulation	CF: Regulation	Standard Error	CF: No Regulation	Regulation	Standard Error
Low-competition markets	226	252	13.18	46	54	4.53
Medium-competition markets	1,046	1,089	21.95	521	562	20.37
High-competition markets	171	102	30.84	141	92	22.8
Number per 10,000	2.08	1.98	.05	2.26	2.16	.05

Note. Low (high) competition is defined as below (above) the 25th (75th) percentile of establishments per capita in the baseline. Medium competition is in the middle 50 percent of outcomes in the baseline. Standard errors of the difference between the baseline and the counterfactual values are calculated on the basis of 10,000 bootstrap samples. CF = counterfactual.

a high level of competition decreases by between 40 percent and 53 percent as a result of the regulations.

The importance of our analysis is that we estimate the extent to which the regulations impact market structure. The relevance of this is further enhanced by recent proposals for these types of regulations by more states and at the federal level. While lobbying groups often argue that the regulations help protect franchisees from unfair treatment by franchisors, we show that they also benefit franchisees by limiting the amount of competition each faces. Therefore, we provide evidence that the regulations may represent a form of regulatory capture, 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 the regulations. For example, they may encourage higher-quality entrepreneurs to become franchisees of national chains. This is a clear and important direction for future research.

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