Unobserved heterogeneity in dynamic games: Cannibalization and preemptive entry of hamburger chains in Canada

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We develop a dynamic entry model of multi-store oligopoly with heterogeneous markets, and estimate it using data on hamburger chains in Canada (1970–2005). Because more lucrative markets attract more entry, firms *appear* to favor the presence of more rivals. Thus unobserved heterogeneity across geographical markets creates an endogeneity problem and poses a methodological challenge in the estimation of dynamic games, which we address by combining the procedures proposed by Kasahara and Shimotsu (2009), Arcidiacono and Miller (2011), and Bajari, Benkard, and Levin (2007). The results suggest that the omission of unobserved market heterogeneity attenuates the estimates of competition, and the trade-off between cannibalization and preemption is an important factor behind the evolution of market structure.

Keywords. Dynamic oligopoly, entry and exit, entry deterrence, market structure, preemption, unobserved heterogeneity.

JEL classification. L13, L81.

1. Introduction

We develop a dynamic entry model of multi-store oligopoly with heterogeneous markets, and estimate it using data on hamburger chains in Canada (1970–2005). The possibility of unobserved heterogeneity across markets is a common cause of concern in many empirical settings, and introduces a particularly severe endogeneity problem in the context of entry and market structure as it leads to biased estimates of competition. Our data feature puzzling patterns in which firms *appear* to favor the presence of

more rivals, presumably because (unobservably) more lucrative markets attract more entry. Indeed, our preliminary regressions suggest models without unobserved market heterogeneity generate attenuated estimates of competition.

The static entry literature such as Berry (1992) has already demonstrated the severity of the endogeneity problem and solved it by a simulation estimator that assumes an order of entry, but addressing this problem in the estimation of a dynamic oligopoly model poses a methodological challenge. Standard two-step approaches such as Bajari, Benkard, and Levin (2007) require nonparametric estimation of equilibrium strategies in the first stage. With unobserved market heterogeneity, these strategies become conditional on unobserved market types and difficult to estimate. A quick solution to this problem is to impose some parametric restrictions on the conditional choice probabilities (CCPs) to ameliorate the data requirement, and either incorporate market fixed effects or estimate CCPs by market (e.g., Suzuki (2013)).

In the presence of dynamic strategic interactions among multi-store firms, however, equilibrium entry strategies could be nonmonotonic in a complicated manner, so parametric restrictions would be inconsistent with the equilibrium play of the game. More specifically, researchers have studied entry and exit at the firm level in both static and dynamic frameworks (e.g., Bresnahan and Reiss (1991), Berry (1992), Mazzeo (2002), Seim (2006), Ciliberto and Tamer (2009), Ryan (2012), and Collard-Wexler (2013)), but many industries are populated by firms with multiple outlets or products,[1] so entry and exit occur at the outlet/product level at least as often as at the firm level. The incentives for such firms are more complicated than for single-store firms. The entry of new outlets harms the profitability of the existing ones (i.e., cannibalization), but the threat of rivals' entry gives rise to preemption motives.[2] This strategic trade-off may dictate multi-store firms' entry decisions and influence the evolution of market structure over time.

For these reasons, we build on recent methodological advances to systematically incorporate such unobserved heterogeneity in our estimation procedure, in three steps. First, we identify the (minimum) number of market types required to rationalize the state transition patterns across markets by using Kasahara and Shimotsu's (2009) approach. Second, we estimate the firms' entry/exit strategies that are conditional on market types by using Arcidiacono and Miller's (2011) method. Third, we use the estimated strategies and forward simulations to estimate the firms' profit functions and sunk costs of entry following Bajari, Benkard, and Levin's (2007) second-stage procedure. We believe the combination of these three techniques represents a useful empirical tool to measure competition accurately in the presence of endogeneity problems and strategic dynamics.

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[1]We refer to such enterprises as multi-outlet, multi-product, or chain-store firms interchangeably.

[2]Earlier theoretical work on the cannibalization–preemption trade-off includes Schmalensee (1978), Eaton and Lipsey (1979), and Judd (1985). They took a motive in the U.S. Federal Trade Commission's complaint in 1972 against the four largest manufacturers of ready-to-eat breakfast cereal, which charged that "brand proliferation" (i.e., the frequent introduction of new product varieties) resulted in high barriers to entry. Thus the underlying theme of this paper applies to a broader context of competition outside retail services.

Three findings emerge from our structural analysis. First, unobserved heterogeneity across geographical markets significantly affects the firms' profits and introduces attenuation biases in the estimates of competition if not properly accounted for (i.e., the estimated negative impact of other shops' presence on a shop's profit becomes smaller in a model without heterogeneous markets). Second, shops of the same chains compete more intensely with each other than with shops of different chains, which implies that cannibalization is one of the most important considerations for the firms' entry decisions. Third, preemption motives are at least as important as cannibalization in shaping the evolution of market structure. Our counterfactual simulations suggest that without such motives, McDonald's would enter markets less aggressively. Thus an accurate measurement of competition requires a model with multi-store ownership, dynamic strategic interactions, and unobserved market heterogeneity.

We have chosen to study hamburger shops, an archetypical chain business, for three reasons. First, they represent one of the simplest cases of multi-store oligopoly. The provision of homogeneous services is one of the main purposes of retail chains. This institutional feature limits the scope of product differentiation among outlets and, hence, helps us identify the trade-off between cannibalization and preemption in its purest form. Second, hamburger shops compete within relatively small geographical markets. Thomadsen's (2005) estimates suggest only shops within approximately 0.5 miles compete as close substitutes, even in car-obsessed California. Nevertheless, multiple shops of the same chain often compete even within such narrowly defined markets, which provides us with enough data to investigate cannibalization as well as unobserved heterogeneity across geographical markets. Third, store opening/closure is the main strategic dimension of hamburger chains' competitive dynamics, and our interviews suggest cannibalization and preemption are among the most important considerations of their store-development officers.[3] Thus hamburger chains provide us with a clean, feasible, and relevant context for the study of dynamic strategic interactions with unobserved market heterogeneity.

The rest of the paper is organized as follows. The remainder of this section summarizes the related literature and this paper's contributions. Section 2 lays out our model. Section 3 explains the institutional features of the industry and presents descriptive statistics of our data set as well as preliminary regressions. Section 4 shows our estimation approach and results. Section 5 analyzes the effects of cannibalization and preemption on entry by conducting counterfactual simulations. Section 6 concludes. The appendices are included and the Supplements, available in files on the journal website, http://qeconomics.org/supp/478/supplement.pdf and http://qeconomics.org/supp/478/code_and_data.zip, feature sensitivity analysis and other institutional considerations.

1.1 *Related literature*

This paper builds on three strands of literature, namely, market entry, preemption games, and structural estimation of dynamic oligopoly.

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[3]Based on our interviews (in person and by phone) with the store-development officers of various hamburger chains in Canada, conducted on multiple occasions between October 22, 2009 and July 18, 2011.

First, among many papers that study entry, Arcidiacono, Bayer, Blevins, and Ellickson (2015) is the most closely related work in terms of modeling, because they also consider entry dynamics of oligopolistic chain stores. Whereas their main objective is to propose and illustrate the use of a continuous-time framework, we focus on addressing unobserved market heterogeneity and assessing the implications of cannibalization and preemption on market structure. Likewise, Holmes (2011) studies cannibalization from the perspective of Walmart's single-agent problem, whereas oligopolistic interactions including preemption motives are the main feature of our study. In terms of substantive interests, Toivanen and Waterson (2005) analyze the entry patterns of McDonald's and Burger King in the United Kingdom, using a static model without unobserved market characteristics, and find a "positive effect" of rival presence on expected profits. By contrast, this paper explicitly controls for both dynamics and unobserved market heterogeneity, and assesses the extent to which these factors could bias the estimates of competition.

Second, many theoretical papers have studied preemption games, including Fudenberg and Tirole (1985), Riordan (1992), Quint and Einav (2005), and Argenziano and Schmidt-Dengler (2012). Few empirical papers structurally estimate such models, but Schmidt-Dengler (2006) and Igami (forthcoming) do so in the specific context of technology adoption. By contrast, this paper aims to quantify the effect of preemption motives in a more general context of entry and market structure, and assesses their implications for the measurement of competition.

Third, our empirical approach relies on the combination of three recent advances in the estimation of dynamic games (Bajari, Benkard, and Levin (2007), Kasahara and Shimotsu (2009), and Arcidiacono and Miller (2011)). The purpose is to incorporate unobserved market heterogeneity in the CCP-based estimation of dynamic oligopoly, including the procedure to determine the number of market types, which is typically assumed a priori.[4] Our results indicate the presence of significant heterogeneity across markets, and highlight the importance of its inclusion for accurate measurement of competition.

Given these literature contexts, this paper aims to make contributions by combining the recently developed methods to address the major endogeneity problem concerning entry and market structure, and showing that incorporating dynamic strategic interactions and unobserved market heterogeneity significantly alters one's conclusion about competition, which is fundamental to an analysis of any market.

2. Model

This section presents our model. The purpose of this research is to assess and address the endogeneity problem caused by unobserved market heterogeneity. We investigate this issue in the context of a dynamic entry game among multi-store firms in which cannibalization and preemption could play potentially important roles.

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[4]A typical specification is a nonparametric finite mixture with two or three points of support. Aguirregabiria and Mira (2007) considered a parametric finite-mixture specification for unobserved market heterogeneity with only one unknown scale parameter but with 21 unobserved market types. They also detected an attenuation bias in the estimates of competition effects when unobserved heterogeneity is ignored, thereby foreshadowing our findings.

The setting is as follows. Time is discrete with an infinite horizon, $t = 1, 2, \ldots, \infty$. Geographical markets $m = 1, 2, \ldots, M$ are independent of each other[5] and, hence, the following exposition focuses on a particular market m without loss of generality. A finite number of firms, indexed by $i = 1, 2, \ldots, I$, operate finite numbers of outlets ($n_{imt} = 0, 1, 2, \ldots$). The firms' entry/exit decisions in a given period, $a_{imt} \in \{1, 0, -1\}$, will change their numbers of outlets in the subsequent period. Market structure is a collection of n_{imt} across firms, $n_{mt} \equiv \{n_{imt}\}_{i=1}^{I}$. Besides market structure, the demand shifter z_{mt} and market type $\mu_m \in \{1, 2, \ldots, K\}$ also affect the firms' period profits.

The timeline is as follows.

• In each period, in each geographical market, each firm observes the industry state $s_{mt} \equiv (n_{mt}, z_{mt})$, market type μ_m, and the independent and identically distributed (i.i.d.) private cost shocks $\varepsilon_{imt}(a_{imt})$ associated with the discrete choices of entry/exit. These shocks represent the firms' idiosyncratic conditions in terms of real estate information, corporate finance, and other managerial or organizational climate for store-development activities.

• Each firm forms expectations over the evolution in the future of its rivals' decisions $a_{-imt} \equiv \{a_{jmt}\}_{j \neq i}$ and the industry state s_{mt}.

• Based on the current state and these expectations, each firm decides on a_{imt} and earns period profit as a function of the current state and its decision,

$$\Pi_i(a_{imt}, s_{mt}, \mu_m; \psi_i) = n_{imt}\pi_i(s_{mt}, \mu_m; \alpha_i, \theta_i) - C_i(a_{imt}; \kappa_i) + \varepsilon_{imt}(a_{imt}), \quad (1)$$

where π_i is the average profit per outlet (parameterized by α_i and θ_i, and specified in the estimation section) and C_i is the sunk cost of entry/exit that equals κ_+ if $a_{imt} = 1$, 0 if $a_{imt} = 0$, and κ_- if $a_{imt} = -1$. The letter ψ denotes a vector of all parameters, (α, θ, κ).

• Finally, each firm implements its entry/exit decision and the endogenous state evolves according to $n_{imt+1} = n_{imt} + a_{imt}$. The demand shifter evolves exogenously according to some first-order Markov process, $f(z_{mt+1}|z_{mt})$.

Each firm maximizes the present value of its future profits with discount factor $\beta \in (0, 1)$. The following Bellman equation characterizes its dynamic programming problem,

$$\begin{aligned}
&V_i(s_{mt}, \varepsilon_{imt}, \mu_m, \sigma; \psi) \\
&= \max_{\sigma_i(s_{mt}, \varepsilon_{imt}, \mu_m)} \Pi_i(s_{mt}, \varepsilon_{imt}, \mu_m, \sigma; \psi) \quad (2) \\
&\quad + \beta E\big[V_i(s_{mt+1}, \varepsilon_{imt+1}, \mu_m, \sigma; \psi)|s_{mt}, \mu_m, \sigma\big],
\end{aligned}$$

where σ is a Markov-strategy profile that maps $(s_{mt}, \varepsilon_{imt}, \mu_m) \longrightarrow a_{imt} \in \{1, 0, -1\}$ for each firm. After the i.i.d. private cost shocks, ε_{imt}, are integrated out, a Markov-perfect equilibrium (MPE) is σ that satisfies

$$V_i(s_m, \mu_m, \sigma; \psi) \geq V_i(s_m, \mu_m, \tilde{\sigma}_i, \sigma_{-i}; \psi) \quad \forall \tilde{\sigma}_i \neq \sigma_i \quad (3)$$

for all firms, when the firms correctly perceive the transition probabilities of s.

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[5]See Appendix C for the validity of this assumption in the hamburger chain industry.

2.1 *Definitions of cannibalization and preemption*

Cannibalization means competition within a firm. In the context of chain stores, multiple stores of the same chain may compete with each other within a single geographical market. The effect of cannibalization on profits will manifest itself in α_i, which is the parameter that governs the relationship between a store's profit and the presence of other shops. See Sections 4.3 and 5.1 for the specification and operationalization regarding how we measure cannibalization and its effects.

The underlying mechanism for preemption also resides in α_i, because preemptive motives cannot exist unless the presence of rival shops affects the profit of a shop, but preemption is more difficult to measure than cannibalization. We propose measuring the effect of preemptive motives based on the difference in the timing of a firm's store opening when its rivals condition their store-opening actions on the presence of the focal firm's shops and when they do not. In the former case, the focal firm has preemptive motives because its rivals may give up entry once it opens a sufficient number of stores to saturate the market. In the latter case, it cannot influence the rivals' future actions and, hence, will lose preemptive motives for early entry.[6]

To complete this definition, we further specify the counterfactual behavior of rivals (when they do not condition on the focal firm) as the conditional distribution of rival shops *with the number of the focal firm's shops integrated out*. That is, the focal firm competes against the same number of rival shops on average, but their entry/exit actions completely ignore the presence or absence of the focal firm's shops. We have chosen this specification because it does not alter the effective market size for the focal firm and obviates the need to impose ad hoc beliefs on rivals in the counterfactual. See Section 5.2 and Appendix B for further details and the empirical analysis.

2.2 *Identification*

Bajari, Chernozhukov, Hong, and Nekipelov (2009) discuss conditions for nonparametric identification of a dynamic discrete game, with a generic period payoff function $\Pi_i(a_i, a_{-i}, s) + \varepsilon_i(a_i)$, and stress the need for firm-specific payoff shifters to achieve identification. Our model (and data) does not seem to contain such variables and might appear underidentified at a first glance. However, the physical characteristic of store-development investment leads to a natural exclusion restriction based on time lags, namely that the rival chains' actions (store opening/closure) merely alter the state in the next period and do not enter the firm's current payoff, and hence $\Pi_i(a_i, a_{-i}, s) =$

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[6]Tirole (1988, Section 8.6.2) proposes measuring the effect of preemptive motives by the difference in the timing of a monopolist incumbent chain's opening of its second shop in the presence and absence of a potential entrant, based on a stylized timing game between two firms, with an exclusive focus on the opening of the second shop in the market. This measure is useful given the specific context and focus of his model. However, this notion of preemption becomes elusive in a more general setting with multiple chains, each of which may operate multiple outlets in the same market, because the incumbent–entrant distinction becomes blurred and an analyst cannot justify an exclusive focus on the second shop. To guide our subsequent analysis with a more empirically relevant concept, we therefore propose an alternative measure of preemptive motives.

$\Pi_i(a_i, s)$ in our empirical context (see equation (1)). Thus our payoff functions are identified, with $I \times 2$ equations (I players and two choices) and $I \times 2$ free parameters rather than $I \times 2 \times 3^{I-1}$ in their model (see their Sections 2.1 and 3.5).

3. Industry and data

This section explains the industry context and our data set from the hamburger chains in Canada (1970–2005). Anecdotal evidence (Sections 3.1 and 3.2) as well as our preliminary regressions (Section 3.3) suggest cannibalization and preemptive motives are major economic forces behind the firms' entry decisions. These regressions will also highlight the importance of incorporating unobserved heterogeneity across geographical markets to correctly infer the degree of competition.

3.1 *Why hamburger chains*

Hamburger shops have represented an archetypical chain-store business since the 1950's in the United States and the 1970's in Canada, and are therefore an obvious industry for a study of multi-store oligopoly dynamics. Moreover, hamburger chains offer a clean, feasible, and relevant setting to analyze cannibalization and preemption.

First, hamburger chains are among the simplest forms of multi-product (outlet) firms in oligopolistic competition, because the purpose of the franchised restaurant business is to provide homogeneous goods and services. Their efforts to produce identical products have been so successful that *The Economist* magazine routinely uses the prices of Big Macs across countries to analyze foreign-exchange rates (i.e., the Big Mac index), based on the premise of purchasing-power parity.[7] Furthermore, the services and the dining experience are also supposed to be homogenized across outlets. These features limit the scope of differentiation among outlets of the same chain, and hence simplify our task of identifying cannibalization and preemption.

Second, hamburger shops compete in relatively small geographical markets and therefore provide us with sufficient cross-sectional variation for econometric purposes. Thomadsen's (2005) estimates suggest that even in California, where most consumers drive (and hence are willing to travel long distances), only shops within approximately 0.5 miles compete as close substitutes in a statistically significant manner. Defined at this microscopic level, sufficient geographical markets exist for the use of a two-step estimation approach.

Third, entry and exit (i.e., opening and closing of outlets) are the most important strategic decisions for any hamburger chain, and qualitative evidence suggests cannibalization and preemption are their main consideration along with the demographic characteristics of the area. Notwithstanding the extremely local nature of markets, multiple outlets of the same chain frequently compete against each other even within such narrowly defined geographical markets, making cannibalization a real concern. Thus cannibalization and preemption are highly relevant economic forces in the evolution of market structure in this industry.

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[7]See, for example, "The Big Mac index: Bunfight," *The Economist*, February 2, 2013.

3.2 *Data*

Our original data source—archived phone directories—contains the universe of hamburger shops in Canada between 1970 and 2005, with their opening and closing years, as well as locations.[8] We supplement it with the market characteristics from the Canadian Census.[9] We have chosen to focus on the sample of 400 geographical markets from seven major cities (Toronto, Montreal, Vancouver, Calgary, Edmonton, Winnipeg, and Ottawa), which covers the majority of the total Canadian population.[10]

We define a geographical market based on a cluster of shops that existed at any point in time between 1970 and 2005 and were located within a 0.5-mile radius of each other (see Section A.1 for a sensitivity analysis with alternative market definitions). After identifying all such clusters, we make two adjustments. First, we omit downtowns, which typically contain a continuum of areas that are densely populated by shops, because we believe the nature of competition can be radically different in such places. Second, we use Google Maps to manually assess the location characteristics of each of the remaining clusters and refine market definition (e.g., by splitting a cluster into two when it contains a highway or a wide river running through it). These procedures leave 400 clusters in the data, with potential undersampling of central business districts. Nevertheless, the final sample still represents the majority of all shops in the seven cities, and is suitable for the analysis of cannibalization and preemption.

The average number of hamburger shops grew from less than 0.5 during the 1970's to approximately 1.8 in the early 2000's. The five chains operating in Canada are A&W, Burger King, Harvey's, McDonald's, and Wendy's. Except for Harvey's, which is headquartered in Toronto, all other chains are based in the United States and hence do not have "home-towns" in Canada. McDonald's is the largest chain by the number of outlets, and A&W is second, although Harvey's is the second largest in Toronto, its hometown. The other two have considerably less presence in Canada (Table 1). We assume geographical markets are independent of each other, and abstract from supply-chain considerations across markets, based on the empirical evidence in Appendix C. Likewise, we abstract from the contractual details of each shop's operation, based on the empirical evidence in Appendix D.

Table 2 shows that the total number of shops across the five chains rarely exceeds three in any market-year observation, which is consistent with our interviews with the store-development officers of various chains. They repetitively mentioned three as the magic number of shops that would saturate a typical market. This observation appears to corroborate the relevance of our market definition to the actual strategic planning of store openings at these chains.

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[8]See Yang (2014) for more details on data.

[9]Census tracts do not necessarily coincide with our geographical markets (defined in the following paragraph), and hence we match them based on their overlaps in terms of zip code.

[10]We suspect smaller cities may potentially represent qualitatively different empirical settings, the inclusion of which might confound our estimates.

TABLE 1. Summary statistics of 400 markets (1970–2005).

	No. Obs.	Mean	Std. Dev.	Min	Max
I. Number of Outlets					
McDonald's	14,000	0.415	0.664	0	7
A&W	14,000	0.189	0.451	0	4
Harvey's	14,000	0.138	0.362	0	2
Burger King	14,000	0.085	0.289	0	3
Wendy's	14,000	0.073	0.266	0	2
II. Market Characteristics					
Population (thousand)	14,000	23.0	12.0	1.7	80.9
Income (thousand C$)	14,000	51.9	16.7	17.4	191.3
Forward population growth (%)	12,000	1.65	0.99	−0.41	8.78

Note: The dollar values are expressed in 2005 constant Canadian dollars. *Source*: Archived phone directories (Yang (2014)), Canadian Census.

3.3 *Preliminary regressions*

Before estimating a fully dynamic model, we examine the data patterns using the ordered probit regressions of entry/exit decisions,

$$
y_{imt} = \begin{cases} exit, & \text{if } y^*_{imt} \leq c_1, \\ unchanged, & \text{if } c_1 < y^*_{imt} \leq c_2, \\ enter, & \text{if } c_2 < y^*_{imt}, \end{cases} \tag{4}
$$

where c_1 and c_2 are cutoff values and the latent profit,

$$
y^*_{imt} = \gamma_1 n_{imt} + \gamma_2 n_{-imt} + z_{mt}\lambda + \nu_{imt}, \tag{5}
$$

incorporates the number of existing outlets (n_{imt}, n_{-imt}), a vector of demand shifters (z_{mt}), and the i.i.d. standard normal cost shocks (ν_{imt}). The γs and λ are their coefficients.

Table 3 conveys three messages. First, the presence of own shops is negatively correlated with entry (i.e., $\hat{\gamma}_1 < 0$), and the magnitude of this within-chain coefficient is always larger than that of the rival-chain coefficient, $\hat{\gamma}_2$. Thus the existing shops of the same brand appear to be a real concern for the firms. Second, the correlation between entry and the presence of rival-chain shops is also negative (i.e., $\hat{\gamma}_2 < 0$), but only after we

TABLE 2. Summary of market structure.

	No. of All Outlets										Total
	0	1	2	3	4	5	6	7	8	9	
No. of observations	6522	4459	1816	688	299	104	73	25	11	3	14,000
Percentage of sample	46.59	31.85	12.97	4.91	2.14	0.74	0.52	0.18	0.08	0.02	100
Cumulative percentage	46.59	78.44	91.41	96.32	98.46	99.20	99.72	99.90	99.98	100	–

Note: The unit of measurement is market-year.

TABLE 3. Preliminary regressions (ordered probit).

	Dep. Var.: Decision to Enter/Exit			
	(1)	(2)	(3)	(4)
Own-store presence (γ_1)	−0.3108***	−0.6135***	−0.7756***	−0.9281***
	(0.0243)	(0.0281)	(0.0294)	(0.0372)
Rival-store presence (γ_2)	0.0180	−0.2733***	−0.2301***	−0.2984***
	(0.0112)	(0.0174)	(0.0178)	(0.0235)
Population (thousand, λ_1)	0.0017*	0.0253***	0.0259***	0.0233***
	(0.0009)	(0.0038)	(0.0039)	(0.0062)
Income (thousand C\$, λ_2)	0.0022**	0.0165***	0.0176***	0.0149***
	(0.0007)	(0.0021)	(0.0021)	(0.0058)
Forward population growth (%)	−	−	−	0.0723***
	(−)	(−)	(−)	(0.0215)
Market dummies	No	Yes	Yes	Yes
Firm dummies	No	No	Yes	Yes
Cutoff 1 (c_1)	−2.7020	−0.9237	−0.8595	−0.8608
	(0.0460)	(0.2844)	(0.2951)	(0.4973)
Cutoff 2 (c_2)	2.3736	4.3860	4.6121	4.8442
	(0.0421)	(0.2886)	(0.3001)	(0.5016)
Number of observations	70,000	70,000	70,000	60,000
Pseudo R^2	0.0139	0.0743	0.1128	0.1418

Note: For illustration purposes only. Standard errors are given in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Forward population growth is the actual annualized percent change between t and $t + 5$. Alternative time horizons such as 10 years generate similar results. See Appendix A and the Supplement for a series of sensitivity analyses.

include the market fixed effect in columns 2, 3, and 4.[11] This observation highlights the importance of incorporating unobserved heterogeneity across markets, because more shops will enter markets that are attractive (in a manner that is unobservable to the econometrician), thereby generating puzzling data patterns as if the firms preferred markets with more rivals. Third, future population growth is positively correlated with entry, suggesting forward-looking behaviors of the firms. Although we cannot rule out the possibility that future population growth did not matter per se and was simply correlated with some other unobserved factors, we believe this data pattern also suggests the strategic nature of entry decisions. A monopolist would not hurry to enter growing markets until their concurrent sizes justified entry, whereas oligopolists would find themselves in a preemption game and engage in racing behaviors.[12]

   In summary, we see both qualitative and quantitative evidence to believe that the hamburger chains in Canada are best characterized as a multi-store oligopoly with forward-looking entry behaviors, and provide a suitable context to study cannibaliza-

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[11] The positive $\hat{\gamma}_2$ in column 1 is reminiscent of Toivanen and Waterson's (2005) study of hamburger shops in the United Kingdom, in which the authors used a static model without unobserved market characteristics and found a positive effect of rival presence.

[12] See Fudenberg and Tirole (1985), Riordan (1992), Quint and Einav (2005), and Argenziano and Schmidt-Dengler (2012) for the theories of entry timing in preemption games.

tion and preemptive entry. We also recognize the importance of controlling for unobserved heterogeneity across markets, and hence in the next section, we design our empirical approach to estimate a dynamic game with a particular emphasis on incorporating unobserved market types.

4. Estimation

This section presents our three-step empirical approach to estimate a dynamic entry game with unobserved market types. First, we use Kasahara and Shimotsu's (2009) approach to identify the (minimum) number of market types, $\hat{K}$, to rationalize the state transition patterns across markets. Second, we use Arcidiacono and Miller's (2011) method to estimate the firms' entry/exit strategies, $\hat{\sigma}(\mu)$, that are conditional on market types ($\mu = 1, 2, \ldots, \hat{K}$, which are unobservable to the econometrician). Third, we use $\hat{\sigma}(\mu)$ and forward simulations to estimate the firms' profit functions and sunk costs of entry, following Bajari, Benkard, and Levin's (2007) second-stage procedure. The estimates suggest (i) market types matter and affect the chains differently, (ii) McDonald's and the other four chains differ significantly in their profit/cost structures, and (iii) the presence of both same- and rival-chain shops decreases a shop's profitability, but the same-chain competition ("cannibalization") is more intense than the rival-chain competition.

4.1 *Discretizing the state space*

In our application, the industry state is $s_{mt} = (n_{mt}, z_{mt})$, where $n_{mt} = \{n_{imt}\}_{i=1}^{5}$ consists of five chains' number of outlets and $z_{mt} = (z_{1mt}, z_{2mt})$ consists of the total population and average income of the market. The discretization of the state space has to establish a careful balance between the need to capture material changes in the real world and the need to maintain a reasonable number of observations in each bin for estimation purposes, which is akin to the bias–variance trade-off. We determined that four bins appears to be the most reasonable size, based on the following considerations of various grid sizes (between 2 and 10 for *each* state variable). Regarding n_{imt}, the total number of shops in a market rarely exceeds three (see Table 2), and hence {0, 1, 2, 3} covers the relevant range of market structure. Regarding z_{mt}, we divide the empirical supports of z_{1mt} and z_{2mt} into their respective quartiles, which classify the demographic situations of the 400 markets over 35 years into $4 \times 4 = 16$ states. A finer grid is certainly conceivable, but we would also like to refrain from parametric restrictions or excessive smoothing when we calculate the CCPs and transition matrices. The above discretization convention leads to coverage of the entire state space by at least 10 observations per bin, which we found would generate more reliable CCPs. See Section A.2 for a further discussion on discretization.

4.2 *The (minimum) number of market types*

We employ Kasahara and Shimotsu's (2009) approach to identify the minimum number of market types to rationalize the observed state-transition patterns across markets. Kasahara and Shimotsu (2009) study nonparametric identifiability of finite-mixture

models of dynamic discrete choices, highlighting three determinants of identification: (i) the time dimension of panel data, (ii) the number of values the covariates can take, and (iii) the heterogeneity of the responses of different types to changes in the covariates. Their key insight is that different sequences of covariates imply different identifying restrictions, and hence the presence of covariates provides a powerful source of identification. Furthermore, they extend their results to the case with a lagged dependent variable and dynamic discrete games, which are directly applicable to our model.

Specifically, Kasahara and Shimotsu (2009, Section 3.2) impose stationarity and a first-order Markov property on the transition process of s_{mt}, and assume the panel length is $T \geq 5$, which our model and data satisfy. Under these assumptions, their Proposition 8 shows $\hat{K} \geq \text{rank}(P^*_{\bar{s}})$, where

$$
P^*_{\bar{s}} = \begin{bmatrix} 1 & P_{\bar{s}}(1) & \cdots & P_{\bar{s}}(S) \\ P_{\bar{s}}(1) & P_{\bar{s}}(1,1) & \cdots & P_{\bar{s}}(1,S) \\ \vdots & \vdots & \ddots & \vdots \\ P_{\bar{s}}(S) & P_{\bar{s}}(S,1) & \cdots & P_{\bar{s}}(S,S) \end{bmatrix},
\tag{6}
$$

$$
P_{\bar{s}}(s) = \Pr(s_2 = s, s_1 = s_3 = \bar{s}),
\tag{7}
$$

$$
P_{\bar{s}}(s, s') = \Pr\big((s_2, s_4) = (s, s'), s_1 = s_3 = s_5 = \bar{s}\big),
\tag{8}
$$

S is the size of the state space, $\bar{s}$ is a particular state, and the subscripts denote time period. Their idea is that if s_{mt} follows a first-order Markov process, looking at every other period breaks the dependence of s_{mt} across periods.

Our data contain more than five periods, so we pool multiple five-period subsamples, and find that $\text{rank}(P^*_{\bar{s}}) = 3$ in our application. When we focus on particular five-period subsamples, the rank becomes 2 or 1 occasionally (especially during the first decade in which relatively few entries occurred), but it is 3 in most subsamples and in the pooled sample as well. Likewise, we may construct $P^*_{\bar{s}}$ for different $\bar{s}$, and the maximum of $\text{rank}(P^*_{\bar{s}})$ across all $\bar{s}$ is 3.[13] More formally, Kasahara and Shimotsu (2014) propose an approach for sequential hypothesis testing based on Kleibergen and Paap's (2006) rk statistic. Although the sparsity of $P^*_{\bar{s}}$ matrices in our empirical context seems to limit our ability to apply this test in a comprehensive manner, in principle, one may test a null hypothesis, $H_0 : \hat{K} = 2$, against $H_1 : \hat{K} = 3$.[14] By contrast, $\hat{K} = 4$ has already been rejected as we found $\text{rank}(P^*_{\bar{s}}) = 3$, because these procedures target the *minimum* number of types. Thus our subsequent analysis proceeds with $\hat{K} = 3$, and we will report alternative parameter estimates based on $K = 2$ and 4 as a sensitivity check.

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[13]We encountered a few $\bar{s}$ for which $\text{rank}(P^*_{\bar{s}}) = 4$, but we have reasons to doubt the meaningfulness of these specific $\bar{s}$.

[14]We thank Hiroyuki Kasahara for a thorough orientation on these procedures. To test the null hypothesis $H_0 : \hat{K} = 2$, one needs to estimate a "misspecified" model with $K = 2$ and generate bootstrapped samples. One may compute the rk statistic for each of these simulated samples and compare them to the rk statistic of the actual data. The higher the actual rk statistic relative to its bootstrapped counterparts, the more stringently one may reject the null hypothesis.

4.3 *Entry/exit strategies by market type*

Having identified the (minimum) number of market types, our next task is to estimate the CCPs of entry/exit by market type. We follow Arcidiacono and Miller (2011), who adapt the expectation-maximization algorithm to incorporate unobserved heterogeneity into CCP estimators of dynamic discrete-choice problems. They also show their (first-stage) CCP estimates can be paired with estimators proposed by Hotz, Miller, Sanders, and Smith (1994) and Bajari, Benkard, and Levin (2007) in the second stage.

Specifically, Arcidiacono and Miller's (2011) estimation algorithm iteratively calculates four objects until convergence, as follows. First, the conditional probability that market m belongs to type μ is

$$q_{m,\mu} = \frac{\varpi(\mu)\prod_t\prod_i\prod_j\left[p_{ij}(s_{imt},\mu)f_{ij}(s_{imt+1}|s_{imt},\mu)\right]^{d_{imjt}}}{\sum_{\mu_m}\varpi(\mu_m)\prod_t\prod_i\prod_j\left[p_{ij}(s_{imt},\mu_m)f_{ij}(s_{imt+1}|s_{imt},\mu_m)\right]^{d_{imjt}}}, \tag{9}$$

where $\varpi(\mu)$ is the unconditional probability that a market belongs to type μ, $p_{ij}(s_{imt},\mu)$ is the CCP of firm i taking action j given state s_{imt} in the type-μ market, $f_{ij}(s_{imt+1}|s_{imt},\mu)$ is the transition probability to reach state s_{imt+1} given firm i's action j in state s_{imt} in the type-μ market, and d_{imjt} is the indicator of the choice in the data (i.e., $d_{imjt}=1$ if $a_{imt}=j\in\{1,0,-1\}$ and 0 otherwise). Second, the unconditional type probability is

$$\varpi(\mu)=\frac{1}{M}\sum_m q_{m,\mu}, \tag{10}$$

where M is the number of markets (400 in our data). Third, the conditional choice probability is

$$p_{ij}(s_{imt}=s,\mu)=\frac{\sum_i\sum_m d_{imjt}q_{m,\mu}I\{s_{imt}=s\}}{\sum_i\sum_m q_{m,\mu}I\{s_{imt}=s\}}. \tag{11}$$

Fourth, the state-transition probability is

$$f_{ij}(s_{imt+1}|s_{imt},\mu)=f_{ij}(n_i'|n_i)f_i(n_{-i}'|n_{-i};p_{-ij}(\cdot))f(z'|z), \tag{12}$$

where the first term represents the (deterministic) transition pattern of n_i given firm i's choice j, the second term is firm i's belief over the evolution of its rivals' outlets, and the third term is the transition probabilities of the demand shifter. Arcidiacono and Miller's method iterates over these four objects, (9)–(12), until they stop changing.

Our implementation proceeds based on the following operational specifications. We use frequency estimates for both the choice and the transition probabilities (equations (11) and (12) above), because we aim to recover these probabilities in a flexible manner. The discretization follows the convention in Section 4.1, and we distinguish between the CCPs of McDonald's and those of the other four chains. McDonald's leads the industry
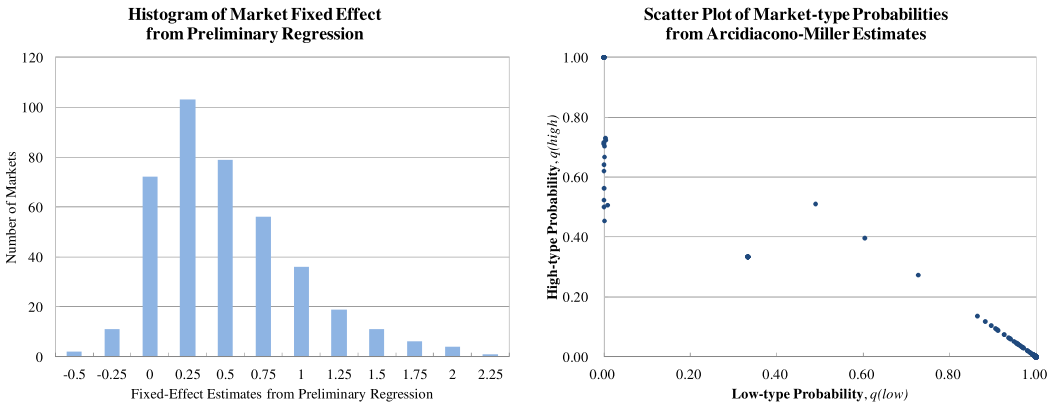
FIGURE 1. Unobserved market heterogeneity. *Note*: The comparison of these two graphs is only for the purpose of qualitative assessment, because the ordered probit (fixed-effect) estimates and the Arcidiacono–Miller-type probabilities are based on substantially different models and methods.

in terms of the number of shops, to the extent that it operates almost as many shops as the four rival chains combined (see Table 1). Thus it seems natural to allow its strategies, profits, and costs to be different from the others. By contrast, the market-year data (with positive number of shops) of the four rival chains become sufficient for estimation purposes (i.e., at least 10 observations exist in each state bin) only after we pool them together. Hence we assume they feature the same profit and cost functions, and follow the same strategies, and we estimate their common CCPs by using their pooled choice data.

Another aspect of operational details concerns how to initialize the algorithm. To our knowledge, no theoretical foundations exist for favoring a particular way to initialize the four objects. Thus what follows simply reflects our intent to avoid completely ad hoc initialization. Specifically, we initialize (10) by using Kasahara and Shimotsu's (2009) factorization equations that accompany their method. We also initialize (11) by assigning the geographical markets in the data into three initial types according to their market fixed-effect estimates from our preliminary regression (column 4 of Table 3), based on which we can calculate the initial CCPs by market type. We start the iterative procedure from these initializations and subsequently update (12), (9), (10), (11), and so on. We also attempted an alternative style of initialization, casually proposed by Arcidiacono and Miller (2011), to use the plain CCP estimates from all markets (i.e., without any notion of market types), and found little change in the results.[15]

This algorithm is straightforward and converges within a relatively short amount of computation time. Figure 1(right) summarizes $[\hat{q}_{m,\mu}]$, the conditional probability that market m belongs to type μ, for all of the 400 markets. Each data point represents a market's probability of being a high and a low type, $(\hat{q}_{m,\text{High}}, \hat{q}_{m,\text{Low}})$, on the vertical and horizontal axes, respectively. Because $\hat{q}_{m,\text{Middle}} = 1 - \hat{q}_{m,\text{High}} - \hat{q}_{m,\text{Low}}$ by construction, a dot's distance from the origin reflects $1 - \hat{q}_{m,\text{Middle}}$ along the 45-degree line. Rel-

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[15]The method does not preclude other styles of initialization, but we prefer basing the initial setting on the data and our preliminary empirical analysis to the extent possible, as a matter of taste.

atively few markets demonstrate high probabilities of belonging to the high-type category, which seems to broadly agree with the skewed distribution of market fixed-effect estimates from our preliminary regressions (Figure 1(left)).[16]

The correlation coefficient between $\hat{q}_{m,\text{High}}$ and the market fixed effect is 0.29, which indicates some nonnegligible updating actually took place in the Arcidiacono–Miller algorithm, so that the final outcome is not totally dictated by the initialization procedure. At the same time, this mildly positive correlation would appear to suggest both the static and the dynamic approaches are shedding light on some genuine market heterogeneity in the data.

Figure 2 summarizes $[\hat{p}_{ij}(s, \mu)]$, the market type-specific CCPs of entry, for a select demographic state (with both z_1 and z_2 in their highest levels, respectively). Three graphs on the left-hand side show McDonald's entry probabilities in high-, middle-, and low-type markets, respectively, and the other three graphs on the right-hand side correspond to those of the other four chains. Three patterns emerge. First, market types matter. Firms enter higher-type markets more frequently, which is the reason we estimate a model with unobserved market types in the first place. Second, McDonald's enters more frequently than its rivals, by a factor of approximately 4. This difference mirrors our earlier observation that McDonald's operates almost one-half of all shops in the data, with the remainder split between the four other chains (Table 1). Third, a higher number of same-chain shops, N_i, reduces the chance of further entry in most cases, highlighting the importance of cannibalization concerns, whereas the impact of the number of rival-chain shops, N_j, is nuanced and highly nonmonotonic. For example, McDonald's is most likely to open a new shop in high- and middle-type markets when three and two rival-chain shops already exist, respectively, which is consistent with the statements of the store-development officers of these firms that three shops saturate a typical geographical market.[17] This nonmonotonic relationship between entry probability and N_j would appear to caution against the use of more restrictive specifications to estimate CCPs, especially when an analyst suspects the presence of dynamic strategic interactions. The exit CCPs in Figure 3 exhibit such nonmonotonicities as well.[18]

---

[16]This comparison is intended only for qualitative assessment purposes. These two measures of the distribution of market heterogeneity are not directly comparable, because $[\hat{q}_{m,\mu}]$ are type probabilities from the fully dynamic model, whereas the fixed-effect estimates stem from the static regressions for descriptive purposes. Also note that although we label three types as high, middle, and low, there does not necessarily exist an obvious rank order of types in either Kasahara and Shimotsu's (2009) or Arcidiacono and Miller's (2011) approaches, and hence some markets may belong to both "high" and "low" with positive probabilities but not "middle." For further interpretations of this finding, see the discussion of our main results in Table 4.

[17]Based on our interviews (in person and by phone) with the store-development officers of various hamburger chains in Canada, conducted on multiple occasions between October 22, 2009 and July 18, 2011.

[18]The exit strategies in low-type markets feature counterintuitive patterns in which the CCPs are the highest when $(N_i, N_{-i}) = (2, 0)$ and $(3, 0)$. Because firms rarely operate multiple shops in low-type markets in the first place (see negligible entry CCPs in Figure 2), these cells represent low-probability events. Thus we suspect our exit CCP estimates for low-type markets might be picking up some unusual data patterns such as a chain's massive entry efforts in a "wrong" location that were promptly scaled back (e.g., in an unpopular shopping mall).

FIGURE 2. Arcidiacono–Miller estimates of entry probabilities by market type. *Note*: Each graph represents the CCP estimates of entry when the market's demography features the highest levels of population (z_1) and income (z_2). The other 15 demographic states entail their own CCP estimates, but the three qualitative patterns (see text) are similar, and hence we omit them from the display to avoid redundant graphs.

In summary, our estimates of the equilibrium strategies corroborate our view that both market types and firm heterogeneity matter, and that cannibalization and preemption could be the key determinants of entry behaviors. We will use these CCP estimates to recover the underlying profit and cost functions in what follows.
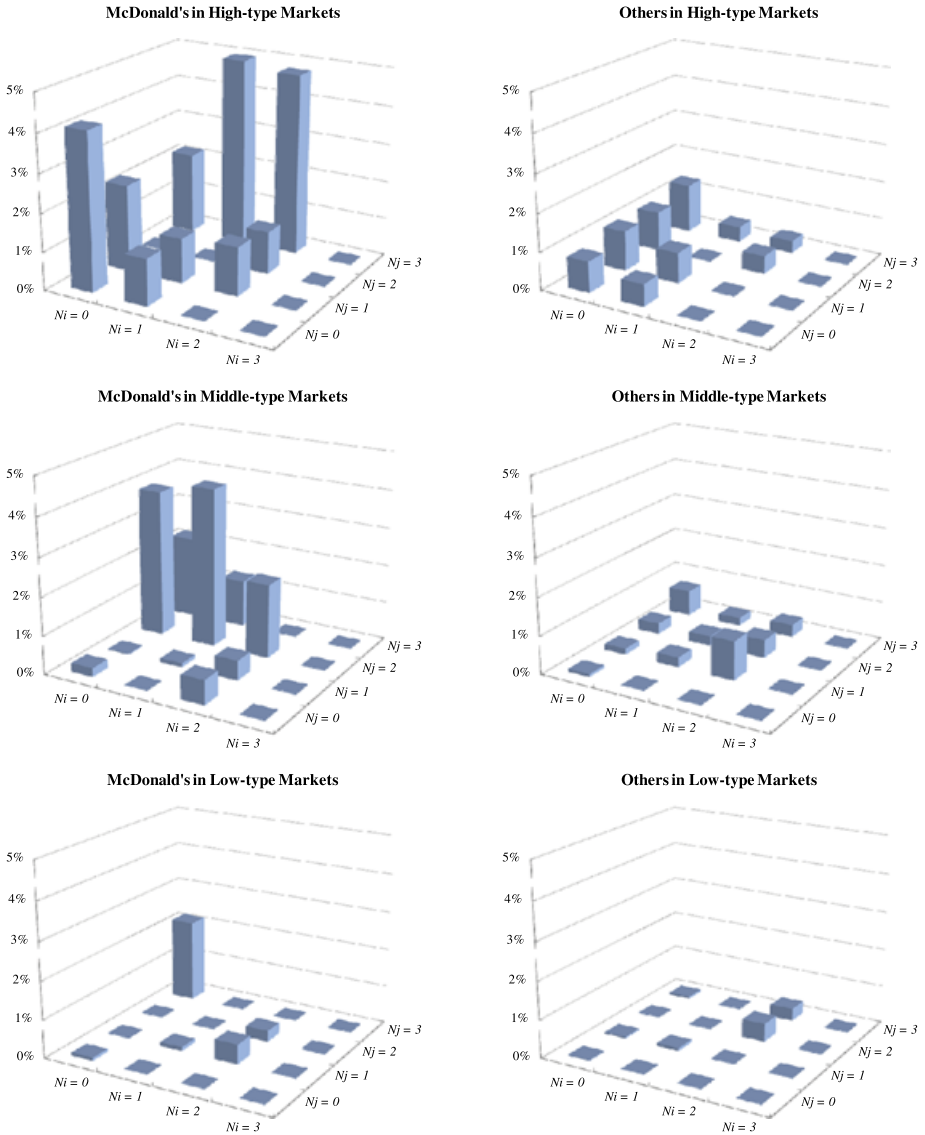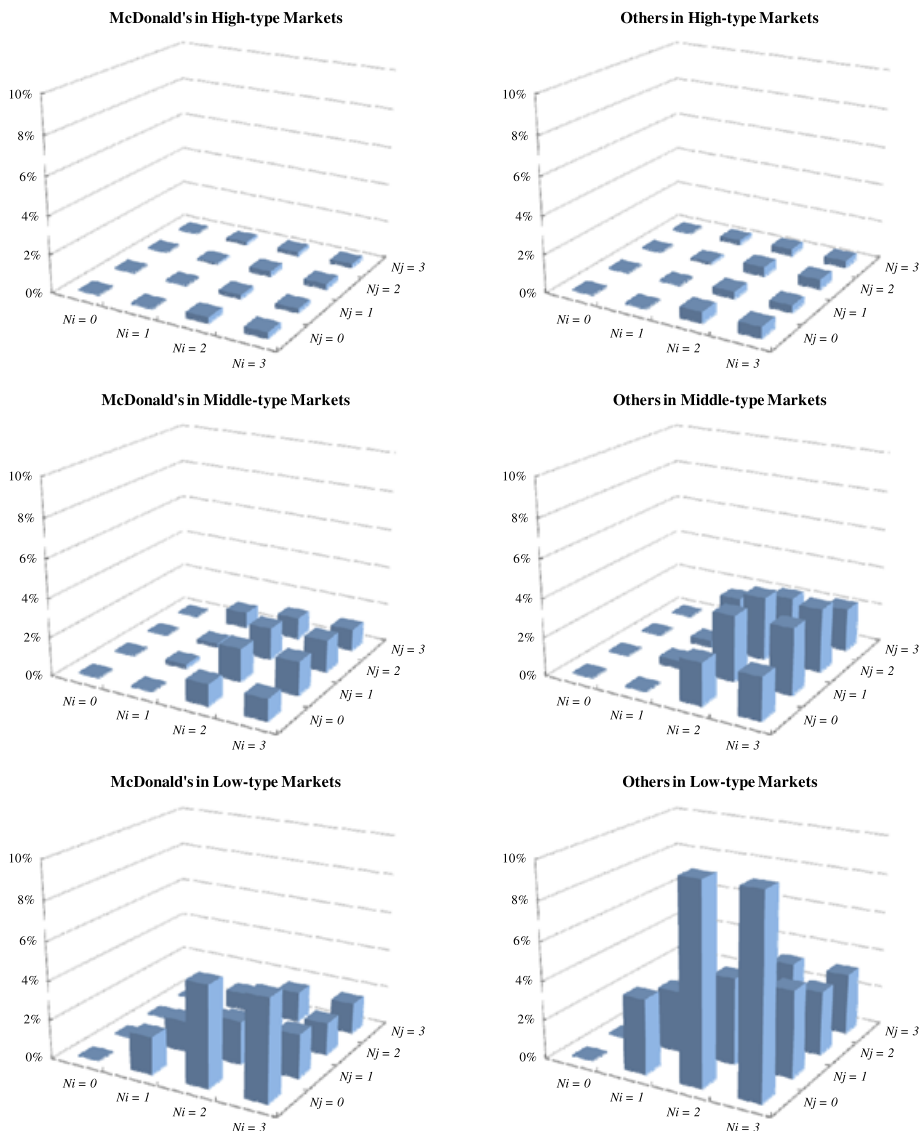
FIGURE 3. Arcidiacono–Miller estimates of exit probabilities by market type. *Note*: Each graph represents the CCP estimates of exit when the market's demography features the highest levels of population (z_1) and income (z_2). The other 15 demographic states entail their own CCP estimates, but their qualitative patterns are similar, and hence we omit them from the display to avoid redundant graphs.

4.4 *Profit function and sunk cost*

Having nonparametrically recovered the equilibrium strategies from the data, we can proceed to estimate the firms' profits and sunk costs by using Hotz et al.'s (1994) and Bajari, Benkard, and Levin's (2007) forward-simulation approach. Intuitively, the underlying idea is to find the values of the parameter vector ψ that would best rationalize the

observed equilibrium strategies, $\hat{\sigma}(\mu)$, in the sense that $\hat{\sigma}_i(\mu)$ delivers higher expected payoffs $\overline{V}_i(s, \mu, \hat{\sigma}; \psi)$ than any other $\overline{V}_i(s, \mu, \tilde{\sigma}_i, \hat{\sigma}_{-i}; \psi)$ based on deviating strategies $\tilde{\sigma}_i$: revealed preference. Bajari, Benkard, and Levin (2007) propose to use the estimated MPE strategy profile, $\hat{\sigma}$, and its perturbed versions, $(\tilde{\sigma}_i, \hat{\sigma}_{-i})$, to compute these expected payoffs by simulating the sequences of period profits into the distant future, and by constructing the expected values,

$$
\overline{V}_i(s, \mu, \hat{\sigma}; \psi) = E\left[\sum_{\tau=t}^{\infty} \beta^t \Pi(s_\tau, \varepsilon_\tau, \mu; \psi)\Big| s_t, \mu, \hat{\sigma}\right]
$$

$$
= \frac{1}{NS} \sum_{ns} \sum_{\tau=t}^{\infty} \beta^\tau \Pi_{i\tau}(ns; \mu, \hat{\sigma}, \psi),
$$

(13)

where the expectation is over the evolution of states and $ns = 1, 2, \ldots, NS$ is the index of simulations. Likewise, we can compute the expected payoffs from some strategies that deviate from the MPE strategy, denoted by $\tilde{\sigma}_i$, by perturbing the choice probabilities in $\hat{\sigma}_i$ by $\varrho \sim N(0, \sigma_\varrho^2)$. The MPE assumption in equation (3) requires the following distance metric to be nonnegative,

$$
g_{np}(s, \mu; \psi) \equiv \overline{V}_i(s, \mu, \hat{\sigma}; \psi) - \overline{V}_i(s, \mu, \tilde{\sigma}_i(np), \hat{\sigma}_{-i}; \psi) \geq 0,
$$

(14)

where np is the index of perturbed strategies. We generate each "perturbed" strategy, $\tilde{\sigma}_i(np)$ by adding a random draw ϱ to the estimated choice probability $\hat{\sigma}_i$ in each bin of the discretized state space. We compute $\overline{V}_i(s, \mu, \tilde{\sigma}_i(np), \hat{\sigma}_{-i}; \psi)$ from NP such deviations, denote each distance metric by g_{np}, and construct the objective function

$$
W(\psi) = \frac{1}{NP} \sum_{np} \left(\min\{g_{np}(s, \mu; \psi), 0\}\right)^2,
$$

(15)

which we subsequently minimize to obtain our estimates, $\hat{\psi}$.

Our empirical implementation proceeds based on the specifications $\beta = 0.9$, $NS = 1000$, $NP = 1000$, $\sigma_\varrho = 0.02$, and $\varepsilon_{it}(a_{it}) \sim$ EV1 i.i.d., and under the standard normalization to set $\hat{\kappa}_- = 0$.[19] We follow the standard empirical models of entry and market structure (e.g., Seim (2006)) and specify the average period profit *per outlet* as

$$
\pi_{imt} = \pi(s_{mt}, \mu_m; \alpha^i, \theta^i) = \alpha_1^i(\mu_m) + \alpha_2^i n_{imt} + \alpha_3^i n_{-imt} + \theta_1^i z_{1mt} + \theta_2^i z_{2mt}, \quad (16)
$$

where α_1, α_2, and α_3 represent the base profit, competition with same-chain outlets, and competition with rival-chain outlets, respectively.[20] The z's and θ's denote demand

---

[19]We should carefully interpret $\hat{\alpha}_1$, $\hat{\kappa}_+$, and $\hat{\kappa}_-$ because they are not identical to the primitives of the model ($\alpha_1, \kappa_+, \kappa_-$) and are not separately identified from each other. Under our normalization, $\hat{\kappa}_- = 0$, Aguirregabiria and Suzuki (2014) show $\hat{\alpha}_1 = \alpha_1 + (1 - \beta)\kappa_-$ and $\hat{\kappa}_+ = \kappa_+ - \kappa_-$. That is, the estimate for the fixed component of profit also incorporates the opportunity cost of operation (i.e., of postponing exit), and the gross entry-cost estimate actually represents the *net* cost of entry and exit. See also Supplement Section O.4.

[20]See Supplement Section O.1 for the estimates based on a more flexible functional form.

TABLE 4. Second-stage estimates by the number of market types.

Chain:	McDonald's				Others			
Number of Types (K):	One	Two	Three	Four	One	Two	Three	Four
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Base profit (α_1)	1.036	8.456	4.272	4.242	1.670	2.087	3.109	3.081
	(0.053)	(0.002)	(0.560)	(0.358)	(0.089)	(0.003)	(0.358)	(0.358)
Type-2 market	–	−1.982	−0.594	−0.537	–	−1.144	−0.754	−0.751
	(–)	(0.003)	(0.099)	(0.120)	(–)	(0.002)	(0.120)	(0.120)
Type-3 market	–	–	−3.801	−3.962	–	–	−1.377	−1.514
	(–)	(–)	(0.830)	(0.158)	(–)	(–)	(0.158)	(0.275)
Type-4 market	–	–	–	−4.227	–	–	–	−1.519
	(–)	(–)	(–)	(0.275)	(–)	(–)	(–)	(0.158)
Own competition (α_2)	−0.109	−0.105	−0.356	−0.301	−0.974	−1.324	−2.000	−1.970
	(0.023)	(0.003)	(0.043)	(0.375)	(0.086)	(0.003)	(0.375)	(0.375)
Rival competition (α_3)	−0.220	−0.133	−0.237	−0.227	−0.172	−0.119	−0.241	−0.263
	(0.010)	(0.003)	(0.010)	(0.012)	(0.025)	(0.002)	(0.012)	(0.012)
Population (θ_1)	−0.015	0.034	0.004	−0.010	−0.050	−0.071	−0.088	−0.080
	(0.009)	(0.003)	(0.010)	(0.025)	(0.017)	(0.003)	(0.025)	(0.025)
Average income (θ_2)	0.001	0.011	−0.030	−0.015	−0.080	−0.059	−0.171	−0.128
	(0.011)	(0.003)	(0.023)	(0.041)	(0.022)	(0.003)	(0.041)	(0.041)
Net entry sunk cost (κ)	9.904	72.432	33.976	34.434	10.555	11.223	13.114	13.395
	(0.269)	(0.001)	(4.932)	(0.419)	(0.262)	(0.003)	(0.420)	(0.419)

Note: Exit cost is normalized to zero, and hence we should interpret κ as the *net* sunk cost. Standard errors are from bootstrapping across markets. The value of the objective function at our preferred estimate (columns 3 and 7 together) is $W(\hat{\psi}) = 29.7499$.

shifters and their impacts on profits. In terms of firm heterogeneity, we will focus on the distinction between McDonald's and the other four chains, for the same reasons we explained in Section 4.2. In addition, we impose a simplifying assumption that the presence of rival-chain shops affects a store's profit symmetrically (i.e., $\alpha_3^{ij} = \alpha_3^i \ \forall j \neq i$, where α_3^{ij} represents the effect of chain j's shop on chain i's shop), so that $n_{-imt} = \sum_{j \neq i} n_{jmt}$ becomes a sufficient statistic for rival-chain competition. Conceptually, nothing prevents us from constructing another layer of the structural model (with richer patterns of cross-brand substitution) underlying this store-level period profit function (16), but the data constraint limits the extent to which we can plausibly identify such additional structures (see Section 4.2 for details).

Columns 3 and 7 of Table 4 show the estimates of the profit functions and sunk costs based on our preferred model with $\hat{K} = 3$, and contain three findings. First, the estimates for $\hat{\alpha}_1(\mu)$ suggest that market types matter and they affect the chains differently.[21] By contrast, columns 1 and 5 show the results without market types (i.e., $K = 1$), which seem to feature somewhat attenuated parameter estimates. Second, substantial

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[21]The market type-specific intercepts for McDonald's and its rivals are (4.272, 3.109), (3.678, 2.355), and (0.471, 1.732) in high-, middle-, and low-type markets, respectively, which means low-type markets are *relatively* more profitable for non-McDonald's chains. This asymmetry seems to explain our earlier finding in Figure 1(right) that some markets exhibit positive probabilities of belonging to high and low types but not middle. That is, such cases represent markets in which non-McDonald's chains are more active than in

heterogeneity exists between McDonald's and the other four chains. McDonald's has to incur higher sunk costs on average ($\hat{\kappa}^{\text{mcd}} > \hat{\kappa}^{\text{other}}$), but it also earns higher profits ($\hat{\alpha}_1^{\text{mcd}} > \hat{\alpha}_1^{\text{other}}$) with the exception of low-type markets. This finding appears consistent with the industry common knowledge that McDonald's invests heavily in many aspects of the hamburger restaurant business, including kitchen equipment, employee training, and store development (Love (1995)). Third, a shop's profit decreases with the presence of other shops (i.e., $\hat{\alpha}_2 < 0$ and $\hat{\alpha}_3 < 0$). This competitive effect is stronger among shops of the same chain than of rival chains (i.e., $\hat{\alpha}_2 < \hat{\alpha}_3 < 0$), making cannibalization one of the most important determinants of profits. We should also note that $\hat{\alpha}_3^{\text{mcd}}$ and $\hat{\alpha}_3^{\text{other}}$ are almost identical and reside within the standard error of each other, which leads us to doubt that a more detailed account of cross-brand substitution patterns would alter our findings materially. Finally, the two demographic variables do not appear to affect profits in a systematic manner. We suspect the sparsity of entry/exit data might be limiting the extent to which we can estimate their effects precisely (see Section A.2 for further details).

What happens if we misspecify the extent of unobserved heterogeneity across markets? Our baseline analysis uses Kasahara and Shimotsu's (2009) method to determine the number of unobserved market types ($\hat{K} = 3$), but previous research has typically imposed some ad hoc K's. In a similar manner, we could (wrongly) assume $K = 2$ or 4 and investigate the consequences of such misspecification.

Columns 2, 4, 6, and 8 of Table 4 show that both the two- and four-type models lead to qualitatively similar parameter estimates, with three noteworthy patterns. First, the type-specific intercepts, $\hat{\alpha}_1(\mu)$'s, suggest the two-type model collapses the middle and low types (in our baseline, three-type model) into a single type (type 2), with the new intercepts lying between those of the two types, whereas the four-type model introduces a redundant type (type 4) that appears statistically indistinguishable from type 3. Second, the competition parameters, $\hat{\alpha}_2$ and $\hat{\alpha}_3$, seem attenuated in the two-type model, which is a result reminiscent of the preliminary regression without market dummies (column 1 of Table 3) as well as the structural estimates without market types (columns 1 and 5 of Table 4). Moreover, their relative magnitudes are reversed for McDonald's (i.e., $\hat{\alpha}_3^{\text{mcd}} < \hat{\alpha}_2^{\text{mcd}}$), which appears counterintuitive. Third, the four-type results closely resemble our three-type baseline. These comparisons suggest that two types are not sufficient to capture the underlying heterogeneity across markets, whereas the inclusion of the fourth type is redundant.

Figure 4 plots the evolution of the number of shops to assess the fit of the estimated model with $\hat{K} = 3$. The model-generated MPE is based on a particular configuration of Pakes and McGuire's (1994) algorithm and is not guaranteed to be unique, so the sole purpose of this exercise is to show that an MPE with a similar trajectory of n_t exists. See Supplement Section O.3 for further discussions.

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other markets *relative to* McDonald's, which could be an indication of consumers' taste heterogeneity as an underlying mechanism behind market heterogeneity.
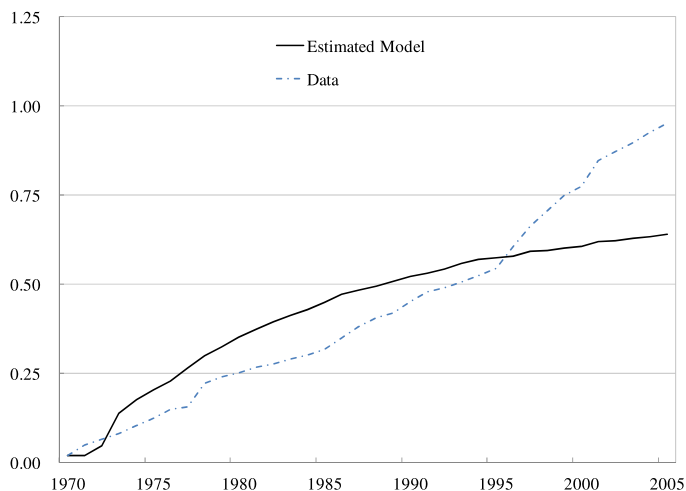
FIGURE 4. The average number of McDonald's per market. *Note*: The model path shows the mean number of shops across 1000 simulations (in each of the 400 markets) based on the model-generated MPE strategies.

4.5 *Identifying assumptions*

Before proceeding to the counterfactual simulations, this subsection will discuss three important assumptions that, if not satisfied, can be potential sources of biases.

First, we assume the unobserved market types are time-invariant. To the extent that the observed characteristics (i.e., population and income) capture important changes at the market level, this assumption is not restrictive. However, if some unobserved factors (e.g., traffic patterns and ethnic composition) had drastically altered the latent demand for hamburgers in some neighborhoods in the middle of the sample period, the restaurant chains might have responded by entry/exit at the time of changes in types. Thus this assumption may not always be valid and can be a potential source of biases.

Arcidiacono and Miller's (2011) approach allows time-varying market types in principle, but we have chosen to assume constant market types for three reasons. The first reason is conceptual and relates to our first step of analysis. We intend to keep our model consistent across the three steps of our empirical analysis. Specifically, we identify the (minimum) number of market types in our first step based on Kasahara and Shimotsu's (2009) approach, which assumes time-invariant types. The second reason is more practical and relates to our second step of analysis. Entry and exit entail large sunk costs and hence are infrequent events even for the large fast-food chains. By allowing entry/exit strategies to vary by three market types and two firm types (i.e., McDonald's vs. the other four), we are already demanding a lot from the relatively sparse data in our estimation task. The third reason is that we expect the biases to be minor because the Arcidiacono-Miller approach (as we currently implement it) estimates the *probabilities* that each market belongs to the three types, $q_{m,\mu}$ (see equation (9)). Even if markets in reality had spent different lengths of time in multiple types, $\hat{q}_{m,\mu}$ would adjust accordingly to reflect different degrees to which market m belonged to type μ. Thus, although

the severity of potential biases is theoretically unknown, we have conceptual as well as practical reasons to prefer our current assumption of time-invariant market types.

The second important assumption is stationarity. We assume both the consumers' preferences and the restaurant chains' technologies remain constant in the fast-food hamburger business during our sample period (1970–2005) in Canada's seven major cities. In reality, tastes may change and important innovations could have occurred, but we doubt Canadians took decades to acquire their true tastes for fast-food hamburgers or that new technologies (e.g., new kitchen equipment, toys and playgrounds for kids, new methods of location hunting, or novel management practices) revolutionized the core production process.[22]

Third, we assume the firms play the same equilibrium, conditional on market types. Geographical markets may vary by their demographic features and the realized configuration of shops but share the same MPE as long as they belong to the same market type. In other words, we allow three different equilibrium plays of the game parameterized by the unobserved profitability of the market, $\alpha_1^i(\mu_m)$, in equation (16). Had the data manifested any obvious symptom of more equilibria, the Kasahara–Shimotsu approach would have indicated more than three types to rationalize it. Our alternative estimate with four market types suggests the fourth type is redundant. Although we can consider additional types/equilibria at the conceptual level, they will not be observationally distinguishable. Thus we do not expect our equilibrium assumption to be a source of biases.

5. Effects of cannibalization and preemptive motives

The strategic trade-off between cannibalization and preemption makes the analysis of chain stores complicated and intriguing. In this section, we assess the implications of cannibalization and preemption on market structure by comparing the entry patterns in the estimated model with those under hypothetical settings in which cannibalization and preemptive motives are muted.

5.1 *Less cannibalization*

How does cannibalization affect market structure dynamics? Cannibalization appears to be a real concern for chain stores, according to our interviews with their store-development officers, as well as our structural estimates of the firms' profit functions. These parameter estimates convey the relative importance of each factor in an abstract measure (i.e., normalized profit functions based on $\varepsilon_{imt} \sim \text{EV1}$ and $\kappa_- = 0$), but ideally we would like to obtain a more direct measure of the cannibalization effect to illustrate its implications on competition.

For these reasons, this subsection examines the evolution of market structure when shops that belong to the same chains do not cannibalize as much as in the baseline

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[22]Our preliminary regressions exhibit a mild time trend but negligible changes in coefficient estimates with or without time trend/dummies, and hence we expect any manifestation of nonstationarity to be a minor source of biases. See Section A.2 for details.
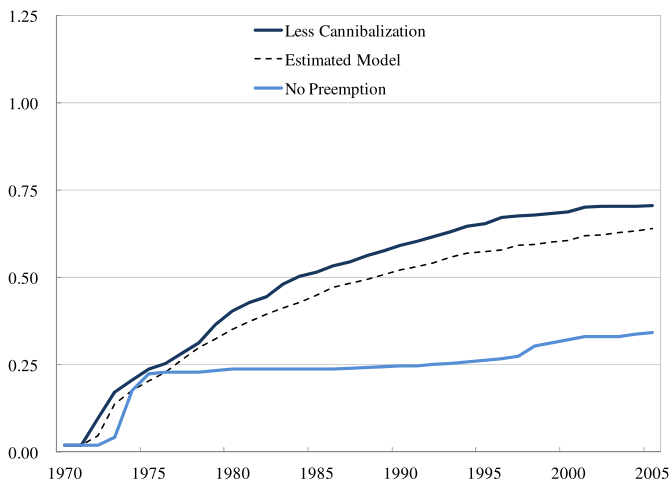
FIGURE 5. Counterfactual number of McDonald's. *Note*: The model and counterfactual paths show the mean number of shops across 1000 simulations (in each of the 400 markets) based on the model and counterfactual strategies, respectively.

model. Specifically, we solve an alternative model in which $\tilde{\alpha}_2 = \hat{\alpha}_3$ for each firm; that is, same-brand shops will no longer be particularly close substitutes as in the baseline estimates.

Figure 5 (dark solid line) suggests that without strong cannibalization, the firms would open shops more aggressively. The average number of McDonald's would surpass 0.5 by 1984, which is 5 years earlier than the baseline, and the level of $\tilde{n}_{2005}^{\mathrm{mcd}}$ would be higher by 10.5%. Thus cannibalization appears to be an important force that slows the chain stores' entry process. The profit-function estimates in Table 4 already foreshadowed this pattern, so the result is not particularly surprising by itself. Nevertheless, we believe constructing the counterfactual history of market structure is valuable because it suggests the extent to which competition estimates based on simple models could be biased.

As we explained in the discussion of fit (Section 4.4), a model-generated MPE is not necessarily unique, and hence this particular counterfactual exercise should be interpreted only as an attempt to construct one (out of many possible versions of) dynamic implication of the estimated model. That said, we paid attention to the computational details of the MPE, so that both the baseline and counterfactual trajectories are generated from exactly the same coding configuration with respect to the initial conditions and other details of numerical search for optimal strategies.

Although detailed analysis of product differentiation is beyond the scope of this paper, one practical implication of this finding is that chain-store operators might have incentives to "diversify" brands to keep growing profitably. A "diversified chain store" might sound contradictory, because uniformity characterizes a chain operation. However, this defining characteristic does not preclude a retailer from operating multiple

chains (brands) of stores. The prevalence of multi-brand operation in practice seems to corroborate this view.[23]

5.2 *When McDonald's cannot affect its rivals*

Despite theorists' attention to preemption games and antitrust practitioners' interest in entry deterrence for over three decades,[24] little empirical work exists on the subject. Besanko et al. (2010) attribute this lack of evidence to the anticompetitive nature of entry deterrence. Because such strategies might violate antitrust statutes, firms would be reluctant to report them especially when they are effective. Another reason is the fact that suitable empirical methodologies to analyze dynamic strategic interactions have been developed only recently. Moreover, preemption is not necessarily an action or outcome, but an underlying *motivation* for taking particular actions in expectation of favorable outcomes in the future, which is why we frequently use the phrase "preemptive motives" instead of "preemption" in this paper. Thus the construction of a no-preemption counterfactual requires attention to the firms' expectations as well as actions.

How would McDonald's entry strategy change in the absence of preemptive motives? We design the no-preemption environment specifically from McDonald's perspective, by making its four rivals nonstrategic players (with respect to McDonald's) who appear and disappear irrespective of n_{mt}^{mcd}, simply according to the conditional distribution of the number of their shops in the data. This distribution is conditional on the demographic variables but integrates out the number of McDonald's. That is, we shut down McDonald's preemptive motives by forcing its rivals to behave as if McDonald's actual entry did not matter, so that McDonald's actions can no longer affect its rivals. When the presence or absence of its stores does not change the rivals' subsequent entry/exit decisions, McDonald's will lose preemptive motives and its optimal entry strategy will differ from the baseline model. We intend to measure this difference as the manifestation of (the lack of) preemptive motives in entry decisions.

Operationally, this counterfactual setting amounts to drawing the number of four rival chains' shops, $n_{mt}^{-\mathrm{mcd}}$, from its empirical distribution conditional on the demographics (but with the number of McDonald's, n_{mt}^{mcd}, integrated out). From the perspective of McDonald's, its rivals become part of nature, and $n_{mt}^{-\mathrm{mcd}}$ evolves exogenously just like z_{mt}. Thus McDonald's solves what has effectively become a single-agent dynamic programming problem. McDonald's cannot influence its rivals, but the latter's presence will still hurt the former's profits, so this exercise isolates McDonald's preemptive motives

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[23]Yum! Brands would be an example of multi-chain operation in the fast-food industry. The company owns KFC, Pizza Hut, and Taco Bell, among others. Likewise, Darden Restaurants is the world's largest full-service restaurant company, with more than 2000 outlets, operating a horizontally diversified set of casual-dining chains including Olive Garden, Long Horn Steakhouse, Red Lobster, Bahama Breeze, Seasons 52, Eddie V's Prime Seafood, The Capital Grille, and Yard House. In a broader set of retail sectors, we can find more vertically differentiated portfolios, such as various lines of hotel brands owned by Hilton Worldwide, which range between luxury, full-service, and select-service categories. Supermarket operators have also relied on multiple store formats, from supercenters to convenience stores (e.g., Carrefour Express, Tesco Express, and Walmart Express).

[24]See the introductory section for the theoretical literature and its competition-policy background.

while preserving the possibility of McDonald's being preempted by its rivals. Moreover, McDonald's is still competing against the same number of rival shops as in the data on average, and hence this counterfactual does not alter the effective market size for McDonald's. Note that this operationalization is only one of several possible ways to compute a preemption effect. We discuss this definitional issue in Section 2.1 and report alternative counterfactual simulations in Appendix B.

Figure 5 (light solid line) shows that without preemptive motives, McDonald's would enter with lower probabilities. For example, its average number of shops would reach 0.25 in 1992, more than 10 years after it does in the estimated model. These results suggest preemptive motives lead to substantially earlier entry in terms of timing, and more competitive market structure at a given point in time.[25]

6. Conclusion

This paper empirically assessed the endogeneity problem caused by unobserved market heterogeneity in the estimation of dynamic games. We showcased the combination of three recent methodological advances within the archetypical entry/exit context of hamburger chains, in which cannibalization and preemption affect firms' forward-looking behaviors. The results suggest that the omission of unobserved market heterogeneity tends to attenuate the estimates of competition, and the dynamic strategic trade-off between cannibalization and preemption plays an important role in the evolution of market structure. These results appear to caution against the use of simpler frameworks in the empirical context of chain stores, which is a common feature of many retail sectors.

Thus a broader implication of this study is that accurate measurement of competition requires explicit considerations of unobserved market types, ownership patterns, and dynamic strategic incentives. As simple and familiar as hamburger shops might appear, these three economic forces are fully at play and would confound inference on competition. Conceptually, these factors are not unique to chain stores, and hence we expect the empirical analysis of market structure in a broader set of industries would benefit from the use of extended dynamic oligopoly frameworks.

Appendix A: Sensitivity analysis

This appendix reports our estimates under alternative settings, including market definition (Section A.1), discretization and nonstationarity (Section A.2), and alternative demographic variables (Section A.3).

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[25]Unlike the MPE trajectories of the baseline model and the less-cannibalization counterfactual, this no-preemption counterfactual concerns McDonald's single-agent problem, and hence it represents a unique solution. Comparing this counterfactual with the baseline MPE will bring us back to the possibility of multiplicity of MPE, but we can also use the data trajectory as the benchmark (i.e., comparing the broken line in Figure 4 with the light solid line in Figure 5).

A.1 *Alternative market definitions*

This subsection investigates the sensitivity of our estimates to the definition of geo-graphical markets. Specifically, we construct two alternative data sets that are based on lower (0.25-mile radius) and higher (1-mile radius) distance thresholds, and conduct preliminary regressions as well as the estimation of the full model. As a reminder, our baseline results are based on the 0.5-mile cutoff, because this sphere of competition is the most relevant according to the store-development officers of the hamburger chains, and Thomadsen's (2005) empirical analysis further supports its validity.

Table 5 shows the ordered probit regressions of entry/exit decisions (as in Section 3.3) using three different samples based on the small, medium (baseline), and large market definitions, respectively. Qualitative patterns are similar across samples, but the magnitude of own- (γ_1) and rival-store (γ_2) coefficients becomes smaller with larger market definitions. The same pattern holds for the coefficient on forward population growth, which we incorporated to obtain suggestive evidence of preemption motives. Furthermore, the pseudo R^2's indicate that the fit declines with larger market defini-tions. These results suggest a highly localized nature of competition among hamburger shops.

We repeat the procedures of structural analysis (as in Section 4) using the alterna-tive market definitions, and present the profit-function estimates in Table 6. To ensure comparability across samples, we fix $M = 3$ (three types of markets) as in the baseline results. The pattern echoes that of preliminary regressions. Both the own- (α_2) and rival-store (α_3) competition coefficients exhibit lower magnitude with larger market defini-

TABLE 5. Preliminary regressions by market definition.

Dep. Var.: Decision to Enter/Exit Market Definition:	Small	Medium (Baseline)	Large
Own competition (γ_1)	−0.9963	−0.9281	−0.7456
	(0.0372)	(0.0372)	(0.0335)
Rival competition (γ_2)	−0.3760	−0.2984	−0.2061
	(0.0249)	(0.0235)	(0.0194)
Population (thousand, λ_1)	0.0223	0.0233	0.0198
	(0.0057)	(0.0062)	(0.0057)
Income (thousand C\$, λ_2)	0.0034	0.0149	0.0080
	(0.0053)	(0.0058)	(0.0056)
Forward population growth (%)	0.0888	0.0723	0.0664
	(0.0174)	(0.0215)	(0.0178)
Market fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Number of observations	72,385	60,000	46,810
Pseudo R^2	0.1492	0.1418	0.1289

Note: The number of observations varies by market definition because the latter alters the number of markets by construction (467, 400, and 302 markets for small, medium, and large definitions, respec-tively). Standard errors are given in parentheses. Forward population growth is the actual annualized percent change between t and $t + 5$. Alternative time horizons such as 10 years generate similar results.

TABLE 6. Second-stage estimates by market definition.

Market Definition:	Small		Medium (Baseline)		Large	
Chain:	McDonald's	Others	McDonald's	Others	McDonald's	Others
Base profit (α_1)	7.296	8.800	4.272	3.109	9.124	1.217
	(0.622)	(0.628)	(0.560)	(0.358)	(0.194)	(0.080)
Middle-type market	−0.284	−1.697	−0.594	−0.754	−3.623	−0.736
	(0.077)	(0.210)	(0.099)	(0.120)	(0.996)	(0.335)
Low-type market	−1.032	−0.510	−3.801	−1.377	−7.776	−0.755
	(0.295)	(0.246)	(0.830)	(0.158)	(1.819)	(0.321)
Own competition (α_2)	−1.175	−7.185	−0.356	−2.000	0.006	−0.680
	(0.325)	(0.649)	(0.043)	(0.375)	(0.019)	(0.080)
Rival competition (α_3)	−0.411	−0.836	−0.237	−0.241	0.005	0.023
	(0.046)	(0.098)	(0.010)	(0.012)	(0.005)	(0.013)
Population (θ_1)	−0.007	−0.046	0.004	−0.088	0.031	−0.007
	(0.014)	(0.020)	(0.010)	(0.025)	(0.012)	(0.018)
Average income (θ_2)	−0.079	−0.350	−0.030	−0.171	0.021	−0.094
	(0.033)	(0.093)	(0.023)	(0.041)	(0.021)	(0.038)
Net entry sunk cost (κ)	52.112	14.807	33.976	13.114	79.139	10.224
	(6.288)	(0.633)	(4.932)	(0.420)	(1.678)	(0.203)

Note: Exit cost is normalized to zero, and hence we should interpret κ as the net sunk cost. Standard errors are from bootstrapping across markets.

tions. They become statistically indistinguishable from zero in the estimates based on the large market definition, which is implausible given the attention these chains devote to analyzing the locations of other shops. Thus a distance criterion equal to or greater than 1 mile would appear to be useless for the empirical analysis of competition among hamburger restaurants.

By contrast, the 0.25-mile (small) cutoff generates more comparable estimates with the baseline results, albeit on a slightly exaggerated scale. This observation that closer shops compete more fiercely seems reasonable. The incorporation of shops' distances within a geographical market is beyond the scope of this paper, which focuses on cannibalization and preemption in a relatively parsimonious state space. However, a dynamic extension of Seim's (2006) model, which features various distance bands, might represent a fruitful path to explore more subtle spatial patterns of retail competition in future research.

A.2 *Discretized demographic variables and time trend*

To assess the usefulness of data variations in the discretized demographic variables in a potentially nonstationary environment, this subsection investigates the sensitivity of our preliminary regressions to the discretization and the inclusion of time trend.

Columns 1, 2, and 3 of Table 7 use the original, undiscretized demographic variables, whereas columns 4, 5, and 6 use their discretized versions. Neither the main coefficient estimates (γ_1 and γ_2) nor the pseudo R^2's show much differences between these two

TABLE 7. Preliminary regressions with discretized demographics and time trend.

	With Continuous Demographics			With Discretized Demographics		
	(1)	(2)	(3)	(4)	(5)	(6)
Own-store presence (γ_1)	−0.7756***	−0.8147***	−0.8194***	−0.7366***	−0.8131***	−0.8183***
	(0.0294)	(0.0301)	(0.0302)	(0.0293)	(0.0301)	(0.0303)
Rival-store presence (γ_2)	−0.2301***	−0.2667***	−0.2692***	−0.1897***	−0.2650***	−0.2683***
	(0.0178)	(0.0186)	(0.0189)	(0.0171)	(0.0186)	(0.0188)
Population (λ_1)	0.0259***	0.0100**	0.0086*	0.1770***	0.0029	−0.0048
	(0.0039)	(0.0045)	(0.0046)	(0.0334)	(0.0369)	(0.0373)
Income (λ_2)	0.0176***	0.0014	0.0065*	0.2114***	−0.0005	0.0177
	(0.0021)	(0.0032)	(0.0036)	(0.0231)	(0.0298)	(0.0320)
Year	–	0.0242***	–	–	0.0288***	–
	(–)	(0.0033)	(–)	(–)	(0.0025)	(–)
Year dummies	No	No	Yes	No	No	Yes
Market dummies	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	70,000	70,000	70,000	70,000	70,000	70,000
Pseudo R^2	0.1128	0.1173	0.1274	0.1060	0.1168	0.1268

Note: Standard errors are given in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The units of measurement for population and income are thousand persons and thousand Canadian dollars, respectively, in columns 1, 2, and 3, and quartiles (codified as 1–4) in columns 4, 5, and 6.

sets of regressions. Thus the discretized version of the data seems to retain sufficient informational content of the original without imposing severe biases.

To investigate the extent of potential nonstationarity in the data, we may compare columns 1 and 4 (no time trend) with columns 2 and 5 (with time trend), and columns 3 and 6 (with year dummies). The latter estimates suggest the presence of a mildly positive time trend, but the qualitative patterns of γ_1 and γ_2 do not change. Moreover, λ_1 and λ_2 lose statistical significance and their signs become erratic, which seems to indicate that our baseline specifications already capture most of the time trend by these demographic variables. Thus we believe our main analysis sufficiently controls for potential nonstationarity.

Table 8 further investigates potential nonstationarity by estimating the model by subsample. Specifically, we divide the sample period (1970–2005) into seven 5-year intervals, and reestimate the model leaving out the first interval in column 1, the second interval in column 2, and so forth. The results appear stable across subsamples. A possible exception is the first 5-year interval, the omission of which (in column 1) seems to attenuate the estimates for α's and κ, but the qualitative patterns remain similar.

A.3 *Alternative demographic variables*

To explore the possibilities that population and income might not adequately capture demand, we investigate the sensitivity of our regressions to two alternative measures of population: population density and the number of traffic lights.

TABLE 8. Second-stage estimates by subsample.

Subsample: Chain:	1 McD	2 McD	3 McD	4 McD	5 McD	6 McD	7 McD
Base profit (α_1)	3.474	4.116	4.116	4.125	4.197	4.116	4.059
	(0.216)	(0.416)	(0.396)	(0.361)	(0.336)	(0.349)	(0.339)
Type-2 market	−0.628	−0.530	−0.483	−0.537	−0.547	−0.536	−0.516
	(0.168)	(0.077)	(0.084)	(0.064)	(0.072)	(0.074)	(0.074)
Type-3 market	−2.642	−3.663	−3.662	−3.642	−3.732	−3.662	−3.613
	(0.183)	(0.881)	(0.655)	(0.868)	(0.572)	(0.523)	(0.574)
Own competition (α_2)	−0.242	−0.368	−0.337	−0.351	−0.343	−0.345	−0.347
	(0.034)	(0.046)	(0.044)	(0.037)	(0.042)	(0.037)	(0.035)
Rival competition (α_3)	−0.180	−0.260	−0.247	−0.258	−0.257	−0.256	−0.251
	(0.019)	(0.017)	(0.013)	(0.014)	(0.013)	(0.014)	(0.014)
Population (θ_1)	0.006	0.008	0.007	0.005	0.006	0.008	0.016
	(0.011)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)
Average income (θ_2)	−0.041	−0.036	−0.017	−0.040	−0.035	−0.039	−0.031
	(0.012)	(0.018)	(0.017)	(0.018)	(0.017)	(0.020)	(0.016)
Net entry sunk cost (κ)	27.806	31.567	31.944	31.750	32.416	31.752	31.367
	(1.850)	(3.628)	(3.422)	(3.095)	(2.979)	(3.006)	(2.892)
Subsample: Chain:	1 Other	2 Other	3 Other	4 Other	5 Other	6 Other	7 Other
Base profit (α_1)	2.335	3.119	2.932	3.004	2.958	2.979	2.909
	(0.348)	(0.343)	(0.333)	(0.312)	(0.274)	(0.266)	(0.280)
Type-2 market	−0.610	−0.762	−0.756	−0.771	−0.786	−0.752	−0.737
	(0.150)	(0.114)	(0.115)	(0.120)	(0.119)	(0.128)	(0.099)
Type-3 market	−1.199	−1.434	−1.387	−1.393	−1.389	−1.373	−1.361
	(0.123)	(0.193)	(0.206)	(0.155)	(0.165)	(0.156)	(0.163)
Own competition (α_2)	−1.355	−1.934	−1.817	−1.852	−1.825	−1.849	−1.818
	(0.333)	(0.351)	(0.351)	(0.326)	(0.301)	(0.288)	(0.286)
Rival competition (α_3)	−0.067	−0.266	−0.233	−0.245	−0.246	−0.250	−0.248
	(0.020)	(0.014)	(0.010)	(0.012)	(0.011)	(0.011)	(0.012)
Population (θ_1)	−0.065	−0.094	−0.096	−0.088	−0.095	−0.071	−0.052
	(0.025)	(0.029)	(0.026)	(0.026)	(0.022)	(0.026)	(0.025)
Average income (θ_2)	−0.066	−0.187	−0.145	−0.178	−0.149	−0.161	−0.128
	(0.025)	(0.046)	(0.043)	(0.038)	(0.032)	(0.036)	(0.034)
Net entry sunk cost (κ)	13.446	13.666	13.248	13.410	13.282	13.394	13.313
	(0.266)	(0.382)	(0.377)	(0.386)	(0.427)	(0.427)	(0.405)

Note: See text for the construction of the seven subsamples. Exit cost is normalized to zero, and hence we should interpret κ as the net sunk cost. Standard errors are from bootstrapping across markets.

First, census tracts could contain wide variation in their surface areas, and hence population density might serve as an appropriate control for the underlying demand. Table 9 compares the baseline preliminary regression (column 1) with two alternative specifications that incorporate population density either as a substitute for, or in addition to, population (columns 2 and 3). The main coefficient estimates (γ_1 and γ_2) and the pseudo R^2's do not seem to vary much across specifications. The coefficient estimates for the demographic variables (λ_1 and λ_2) also exhibit insignificant changes between columns 1 and 3. An interesting feature of the coefficient estimates for population den-

TABLE 9. Preliminary regressions (ordered probit) with population density.

	Dep. Var.: Decision to Enter/Exit		
	(1)	(2)	(3)
Own-store presence (γ_1)	−0.7756***	−0.7530***	−0.7760***
	(0.0294)	(0.0291)	(0.0294)
Rival-store presence (γ_2)	−0.2301***	−0.2089***	−0.2301***
	(0.0178)	(0.0174)	(0.0178)
Population (thousand, λ_1)	0.0259***	–	0.0285***
	(0.0039)	(–)	(0.0044)
Population density (per km^2)	–	0.0103**	−0.0070
	(–)	(0.0049)	(0.0056)
Income (thousand C\$, λ_2)	0.0176***	0.0251***	0.0173***
	(0.0021)	(0.0017)	(0.0021)
Market dummies	Yes	Yes	Yes
Firm dummies	Yes	Yes	Yes
Number of observations	70,000	70,000	70,000
Pseudo R^2	0.1128	0.1094	0.1129

Note: Standard errors are given in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

sity is its loss of statistical significance in column 3 (compared with column 2), which could be a symptom of its collinearity with population. Indeed, the correlation coefficient of population and population density is 0.3580, whereas that between income and population density is 0.0608. These patterns suggest the inclusion of population density does not significantly alter our estimates for γ_1 and γ_2.

Second, population statistics typically reflect the number of residents but not necessarily the daytime population, which might be more relevant for hamburger restaurants. Neither the exact size of the daytime population nor its close proxy (e.g., the size of floor space in offices and commercial buildings) is recorded in publicly available statistics,[26] but the number of traffic lights is available for the city of Toronto. Because Toronto is the largest city of Canada, this subsample contains a sufficient number of observations.

Table 10 compares our baseline specification (column 1) with the alternatives that use traffic light information. The main coefficient estimates (γ_1 and γ_2) and the pseudo R^2's do not change materially between columns 1 and 4. The coefficient estimates for population and income (λ_1 and λ_2) do not change significantly either. The changes in the coefficient estimates for traffic lights across columns appear to suggest its collinearity with population, which is reasonable because the correlation coefficient between population and traffic lights is 0.4838, whereas that between income and traffic lights is −0.0127. Thus population seems sufficiently useful, and our findings regarding γ_1 and γ_2 appear robust.

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[26]We thank Lu Han and Victor Aguirregabiria for this information.

TABLE 10. Preliminary regressions (ordered probit) with traffic lights in Toronto.

	Dep. Var.: Decision to Enter/Exit			
	(1)	(2)	(3)	(4)
Own-store presence (γ_1)	−1.2598***	−1.1173***	−1.2230***	−1.2771***
	(0.1010)	(0.0983)	(0.1015)	(0.1028)
Rival-store presence (γ_2)	−0.4130***	−0.2730***	−0.3637***	−0.4183***
	(0.0635)	(0.0566)	(0.0605)	(0.0637)
Population (thousand, λ_1)	0.0510***	–	–	0.0379***
	(0.0090)	(–)	(–)	(0.0116)
Traffic lights (count)	–	0.0558***	0.0418***	0.0194*
	(–)	(0.0074)	(0.0082)	(0.0106)
Income (thousand C\$, λ_2)	0.0189***	–	0.0223***	0.0182***
	(0.0046)	(–)	(0.0044)	(0.0047)
Market dummies	Yes	Yes	Yes	Yes
Firm dummies	Yes	Yes	Yes	Yes
Number of observations	13,825	13,825	13,825	13,825
Pseudo R^2	0.1606	0.1444	0.1569	0.1624

Note: Standard errors are given in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

APPENDIX B: NO-PREEMPTION COUNTERFACTUALS

This appendix reports alternative no-preemption counterfactual simulations.

B.1 *No threat of entry*

As we discussed in Section 2.1, our design of the no-preemption counterfactual differs from Tirole's (1988) operationalization, because the latter is appropriate only for a stylized case in which the identities of an incumbent monopolist and a potential entrant are clear and the analytical focus is exclusively on the timing of the second shop's opening. Both of these conditions appear too restrictive in our empirical setting. Nevertheless, we can implement a Tirolean counterfactual by simply eliminating all rivals.

   Figure 6 compares the Tirolean counterfactual and our preferred counterfactual, both of which are designed to simulate an environment without preemptive motives, but the outcomes differ. The Tirolean counterfactual features more aggressive entry of McDonald's than in our baseline counterfactual, because by eliminating all potential competitors in the future, the former setting enlarges the expected effective sizes of markets for McDonald's. By contrast, our preferred counterfactual lets in the rivals in a manner that is comparable to the actual entry patterns in the data (and therefore allows McDonald's to be preempted), and hence the residual demand for McDonald's remains the same as in the data on average.

B.2 *Pre-commitment*

One might wonder why we focus exclusively on McDonald's in the setting in which its rivals are not best responding to its new strategy. Why not shut down all firms' preemp-
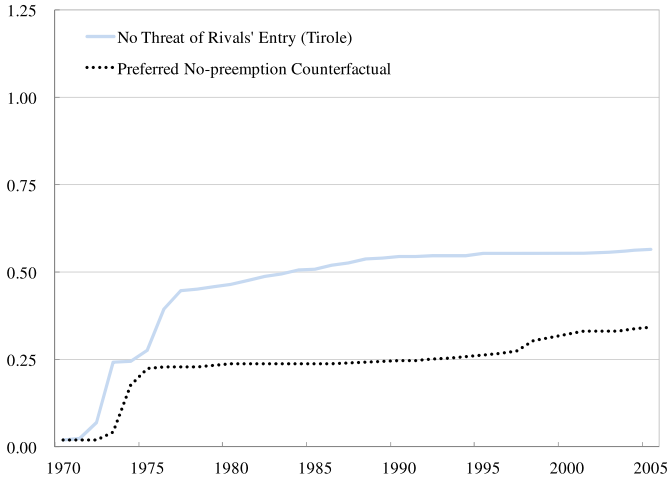
FIGURE 6. No-preemption counterfactual without threat of entry. *Note*: The counterfactual paths show the mean number of McDonald's shops across 1000 simulations (in each of the 400 markets).

tive motives by studying some alternative equilibrium? The reason is twofold. First, preemptive motives exist as long as firms engage in dynamic strategic interactions. In other words, we cannot completely isolate preemptive motives when firms' entry decisions are best responses to each other, which is why we analyze how a particular firm (McDonald's) changes its best response when its rivals stop responding to it. Second, open-loop Nash equilibrium is a common alternative to MPE (e.g., Dockner, Jorgensen, Van Long, and Sorger (2001)) and is often used to shut down some aspects of dynamic strategic interactions. However, it does not necessarily shut down preemptive motives and can actually strengthen them, as we demonstrate in what follows.

An open-loop Nash equilibrium does not require subgame perfection or optimal state-contingent plans. The literature typically implements it by considering firms' pre-commitment to time-contingent action plans (e.g., Chicu (2012)), thereby shutting down state-by-state reactions among firms. However, we should note that firms are still best responding to each other at time zero in terms of their time-contingent plans. If a firm knows the other firms are planning to enter at certain points in the future, it would consider entering earlier than them, and the rivals are formulating their time-contingent plans likewise. Thus pre-commitment does not imply the absence of preemptive motives, because firms are still strategically choosing their timing of entry.

Figure 7 shows that pre-commitment actually seems to strengthen preemptive motives. The open-loop equilibrium features disproportionately high entry rates in the first few years, followed by a long period of unchanged market structure. This counterfactual timing pattern is consistent with the absence of *reactive* motives, but inconsistent with the absence of *preemptive* motives, and hence we prefer our analysis in the previous subsection as a study of preemptive motives.

Potentially, multiple open-loop Nash equilibria may exist, and we did encounter a few slightly different open-loop Nash strategies. However, the timing pattern of n_t re-
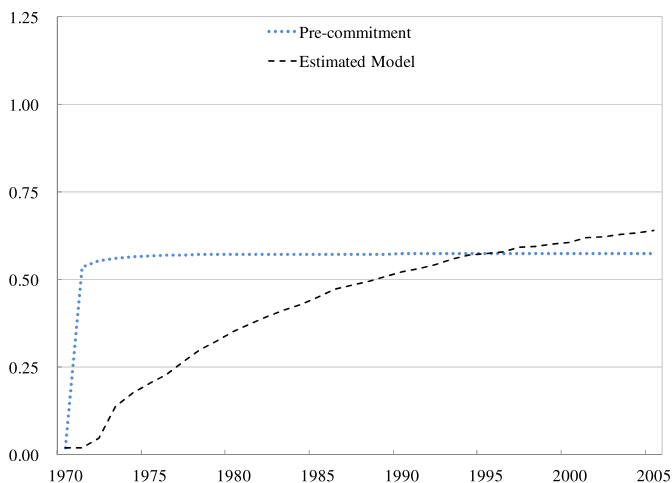
FIGURE 7. Pre-commitment reinforces preemptive motives. *Note*: The counterfactual paths show the mean number of McDonald's shops across 1000 simulations (in each of the 400 markets).

mains unchanged. That is, regardless of the computational details, optimal entry strategies with pre-commitment seem to entail relatively high entry probabilities in the first few years, and practically zero entry afterward.

Appendix C: Absence of supply-chain considerations

We assume geographical markets are independent from each other. This assumption would be problematic if economies of density existed as in Holmes' (2011) study of Walmart, in which he showed a systematic geographical pattern of Walmart's entry that radiates from the headquarters.[27] We investigate this possibility from three directions as follows.

First, Figure 8(left) plots the distance between the headquarters and each new McDonald's shop in Toronto by opening year. If McDonald's preferred a tight network of stores for logistics purposes, the graph would exhibit an upward trend over time, but it does not. Instead, we find a slightly downward trend with low statistical significance, and the adjusted R^2 is 0.0073.

Second, Figure 8(right) plots the distance between each new shop and its nearest existing shop of the same chain. If McDonald's preferred a tight network based on its shops' distance from distribution centers, this graph should demonstrate clustering patterns around certain logistically optimal distances. In fact, new shops are located anywhere between 0 and 10 miles from the nearest existing shops, with a slightly decreasing trend over time (statistically significant at the 1% level) and the adjusted R^2 of 0.1645. Thus cannibalization concerns appear to dominate hypothesized economies of density.

Third, we interviewed a store-development officer at McDonald's specifically on this topic, who explicitly stated, "Decisions made by [the] Real Estate [department] do not

[27]Nishida (2015) also found economies of density in the context of convenience stores in Japan.
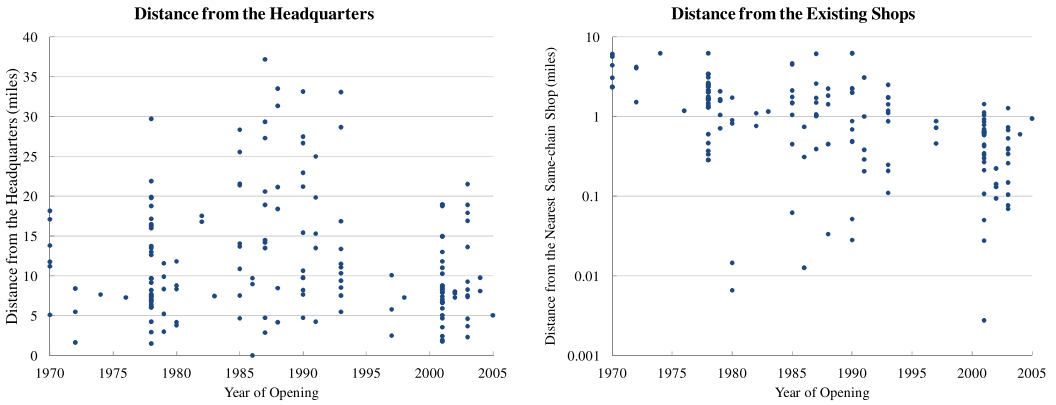
FIGURE 8. Locations of new McDonald's in Toronto. *Note*: The headquarters of McDonald's in Toronto is located at McDonald's Place, M3C 3L4. We calculate the driving distance from each shop using Google Maps. These graphs focus on McDonald's in Toronto for the purpose of illustration, but we find a similar (lack of) geographical pattern in the other six cities, as well as for the other four chains.

take into consideration any supply chain efficiencies," including potential efficiencies in terms of labor and supervision of restaurants. This description of the internal decision process (i.e., stated preference) is consistent with the two data patterns in the above (i.e., revealed preference).

Thus economies of density do not appear to be a primary consideration for the hamburger business, in which highly localized competition dominates other factors.[28] Based on this empirical evidence, we believe our model is useful for capturing important aspects of entry and competition in the hamburger chain industry.

APPENDIX D: PROFITS FROM FRANCHISED AND COMPANY-OPERATED RESTAURANTS

Our data do not contain comprehensive information on the contractual details of the five hamburger chains between 1970 and 2005, and hence our model abstracts from the distinction between franchised and company-operated outlets. This omission could be problematic if these two contractual formats affect the firms' overall profits in a significantly different manner. For this reason, we have chosen to investigate their potentially different profit implications, using publicly available information from annual reports.

Table 11 shows selected items from the income statements and other operation details of McDonald's in the middle of our sample period, with an emphasis on how sales, operating profits, and the number of restaurants compare between franchised and

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[28]In our view, McDonald's and other hamburger chains concentrate their efforts on microlevel location hunting and the sophistication of cooking processes, whereas Walmart and other supercenters seem to compete primarily in the efficiency of purchasing and distribution logistics on a relatively larger geographical scale. In other words, hamburger restaurants and supercenters embody different technologies and operate under different geographical constraints.

TABLE 11. Franchised versus company-operated outlets at McDonald's.

	Year									
	2000	1999	1998	1997	1996	1995	1994	1993	1992	1991
Share of franchised operations (%)										
Number of restaurants	69	72	74	74	76	76	77	78	78	77
Sales	70	71	72	72	73	74	75	75	74	73
Operating profits for company	64	64	64	64	64	65	65	65	63	63
Systemwide operating results										
Number of restaurants	24,447	22,008	20,519	19,084	17,668	15,969	14,160	12,651	11,788	11,282
Franchised	16,795	15,949	15,086	14,197	13,374	12,186	10,944	9,918	9,237	8,735
Company operated	7,652	6,059	5,433	4,887	4,294	3,783	3,216	2,733	2,551	2,547
Sales ($mn)	34,930	33,342	31,225	28,999	27,540	25,986	22,939	20,913	19,577	17,867
Franchised	24,463	23,830	22,330	20,863	19,969	19,123	17,146	15,756	14,474	12,959
Company operated	10,467	9,512	8,895	8,136	7,571	6,863	5,793	5,157	5,103	4,908
Average sales ($mn)	1.4	1.5	1.5	1.5	1.6	1.6	1.6	1.7	1.7	1.6
Franchised	1.5	1.5	1.5	1.5	1.5	1.6	1.6	1.6	1.6	1.5
Company operated	1.4	1.6	1.6	1.7	1.8	1.8	1.8	1.9	2.0	1.9
Consolidated income statement										
Operating profits* ($mn)	4,721	4,692	4,482	4,145	3,954	3,731	3,241	2,863	2,659	2,359
Franchised	3,004	3,009	2,848	2,658	2,546	2,416	2,093	1,871	1,682	1,481
Company operated	1,717	1,683	1,634	1,486	1,408	1,315	1,148	992	977	879

Note: "Operating profits" excludes selling, general, and administrative expenses, as well as other operating costs that cannot be attributed to either franchised or company-operated restaurants. *Source*: McDonald's Corporation Annual Report.

company-operated outlets. For example, in year 2000, the restaurants operated by franchisees accounted for 70% of sales, 64% of operating profits *for the company*, and 69% of the total outlet count. These numbers fluctuate over the years but seem to be well aligned with each other overall, with one exception.

Note that the franchised outlets' contribution to the company's operating profit (63%–65%) is consistently below their shares of sales and the number of outlets (69%–78%), which implies that the franchisees take approximately one-tenth of profits for themselves. This pattern reflects the profit-sharing arrangement between the franchisees and the company, and presumably constitutes an important part of the incentive scheme. Consequently, the possibility remains that the company faces somewhat different expected profits from opening new shops, depending on whether the existing and new shops are operated by franchisees or the company, which could potentially bias our results.

At the same time, we should also consider the magnitude of this profitability difference, which, at approximately 10%, is not negligible but probably does not completely alter the firm's entry decisions either. Our profit function estimates seem to imply the effects of market types and competition could often dominate the subtle difference in contractual arrangements. Moreover, anecdotal evidence suggests that even though franchised outlets contribute relatively smaller profits on average, the companies are not particularly enthusiastic about cannibalizing them, because franchise agreements are an active area of litigation, and one of the most common types of disputes concerns competition with same-chain outlets.

In conclusion, we believe the contractual details are potentially important aspects of chain stores, and we observe some indication of the difference between franchised and company-operated shops in the annual reports. Nevertheless, we also believe our findings would not be particularly sensitive to this distinction, because market size and competition appear to influence the long-run evolution of entry and market structure with larger magnitudes. If more data were available, how the contractual setting interacts with dynamic strategic incentives would be a fascinating question for future research.

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