

# Cannibalization and Preemptive Entry\*

Mitsuru Igami<sup>†</sup>      Nathan Yang<sup>‡</sup>

August 20, 2013

## Abstract

We study cannibalization and preemption in the evolution of market structure. Because a market can accommodate only a finite number of products/outlets, forward-looking firms face the tradeoff between cannibalization and preemption. We develop a dynamic entry model of multi-store oligopoly, and estimate it using data on hamburger chains in Canada (1970–2005). The results suggest cannibalization is the main determinant of profit and entry. Moreover, counterfactual simulations imply preemptive motives generate highly non-monotonic entry strategies, and caution against the use of static approaches when market structure is evolving.

*Keywords:* Dynamic Oligopoly, Entry and Exit, Market Structure.

## 1 Introduction

We investigate how cannibalization and preemption affect new entry and the evolution of market structure. 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, Ryan 2012, and Collard-Wexler 2013). However, many industries are populated by firms with multiple outlets or products,<sup>1</sup> 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-product firms. The entry of new outlets/products harms the profitability of the

---

\*We thank Victor Aguirregabiria, Steven Berry, Philip Haile, Kei Kawai, Robin Lee, Mitsukuni Nishida, Mar Reguant, Qiaowei Shen, Junichi Suzuki, Yasutora Watanabe, and Li Yang, as well as the seminar participants at Yale, the Econometric Society NASM, and the IO Conference at the University of Tokyo for suggestions. We thank the staff at the Toronto Reference Library for their patient data-collection support.

<sup>†</sup>Yale Department of Economics. Email: mitsuru.igami@yale.edu.

<sup>‡</sup>Yale School of Management. Email: nathan.yang@yale.edu.

<sup>1</sup>We refer to such enterprises as “multi-outlet,” “multi-product,” or “chain store” firms interchangeably.

existing ones (i.e., cannibalization), but the threat of rivals' entry gives rise to preemption motives. This strategic tradeoff dictates multi-product firms' decision making in the face of a changing competitive environment, which is in turn shaped by their entry/exit behaviors. We need to study these incentives carefully to better understand competition and market structure, because even the most familiar example of entry/exit (such as hamburger shops) entails multi-store operations. For these reasons, this paper studies cannibalization and preemption in the evolution of market structure, and aims to extend the analysis of entry to incorporate dynamic strategic interactions among multi-outlet/product firms.

To capture these strategic incentives, we develop a dynamic entry model of multi-store oligopoly, and estimate it using a panel dataset of hamburger chains in Canada (1970–2005). Our model features an infinite-horizon dynamic game in which a finite number of firms decides every year whether to increase or decrease the number of outlets. The opening of new outlets reduces the profitability of the existing ones by making the market more competitive, but it also discourages rivals' entry in the future, precisely because new outlets make the market more competitive. An empirical assessment of this cannibalization-preemption tradeoff calls for structural estimation, because revenues and costs are typically unobserved, and both market structure and the entry/exit incentives evolve endogenously in potentially complicated dynamics. Specifically, the relationship between entry and market structure is likely to be non-monotonic, because a firm's entry could also *encourage* rivals to enter when the market is becoming increasingly saturated, which may incentivize firms to engage in racing behaviors. Our data indeed exhibit entry probabilities that are highly non-monotonic in concurrent market structure, which we aim to explain by dynamic strategic incentives.

We have chosen to study hamburger chains for three reasons. First, they represent the simplest case of multi-product 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 tradeoff 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 at multi-product firms. Third, entry/exit (or store opening/closure) is the main strategic dimension of hamburger chains' competitive dynamics, and our interviews suggest cannibalization and preemption are considered the most important considerations of their store-development officers.<sup>2</sup> Thus

---

<sup>2</sup>Based on our interviews (in-person and phone) with the store-development officers of various hamburger chains in Canada, conducted on multiple occasions between October 22, 2009, and July 18, 2011.

hamburger chains provide us with a clean, feasible, and relevant context for the study of cannibalization and preemption with multi-product firms.

We estimate structural parameters of period profit function at the outlet level and the sunk costs of entry/exit by using the two-step approach of Bajari, Benkard, and Levin (2007). The estimates suggest cannibalization (i.e., competition between shops of the same chain) is the single most important determinant of period profits. We then conduct counterfactual simulations in which we hypothetically eliminate preemptive motives from the leading firm’s (McDonald’s) decision making, by modeling its four rivals as non-strategic players that ignore the choices made by McDonald’s: Ronald McDonald against the machines. The resulting optimal strategy of McDonald’s exhibits entry probabilities that monotonically decrease with the number of rivals, which implies preemptive motives can explain the highly non-monotonic entry strategy in the data. This observation is consistent with our qualitative evidence from the interviews in which managers repeatedly spoke of “three” as their magic number of shops that saturate a typical market, and their need to act accordingly.

These findings, together with our preliminary, static regressions, seem to caution against the use of static approaches when market structure is still evolving. Our data suggest markets require at least a couple of decades to reach anything that resembles a long-run equilibrium, even in an industry with a relatively static technology. Under such circumstances with preemptive entry, conventional regressions are doomed to find some “positive effects” of competition on profits, a counter-intuitive conclusion that happens to be common in the literature. Thus our results highlight the importance of incorporating dynamic strategic incentives to understand competition and market structure, even in a seemingly simple empirical setting such as hamburger chains.

The rest of the paper is organized as follows. Section 2 explains the institutional features of the industry and presents descriptive statistics of our dataset, as well as preliminary “static” regressions. Section 3 lays out our model. Section 4 shows our estimation approach and results. Section 5 analyzes the effects of preemption and cannibalization on entry by comparing the data with the no-preemption and no-cannibalization counterfactual simulations. Section 6 features robustness checks and sensitivity analyses. Section 7 concludes.

## 2 Industry and Data

This section explains the institutional features of the industry and our dataset, as well as our non-parametric analysis of the relationship between entry/exit decisions and market structure, which will later serve as the first-stage estimates of the dynamic game (section

4.2).

## 2.1 Why Hamburger Chains

We have chosen to study cannibalization, preemption, and the evolution of market structure in the context of hamburger chains, because they offer a clean, feasible, and relevant setting to empirically assess these economic forces.

First, hamburger chains are among the simplest forms of multi-product (outlet) firms in oligopolistic competition, because the purpose of 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.<sup>3</sup> Furthermore, the services and the “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.

## 2.2 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.<sup>4</sup> We supplement it with the market characteristics from the Canadian Census.

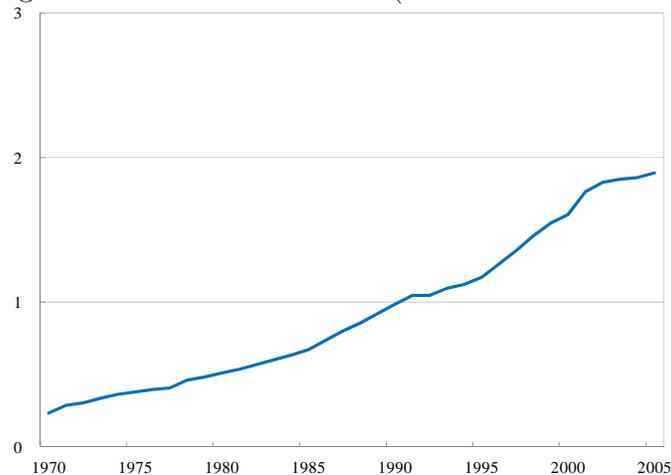
---

<sup>3</sup>See, for example, “The Big Mac index: Bunfight,” *The Economist*, February 2, 2013.

<sup>4</sup>See Yang (2012) for more details on data.

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.<sup>5</sup>

Figure 1: Number of Outlets (Total of Five Chains)



*Note:* Mean of 400 markets.

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 half-mile radius of each other. 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 under-sampling 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 preemption and cannibalization.

The average number of hamburger shops grew from less than 0.5 during the 1970s to approximately 1.8 in the early 2000s (Figure 1). 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).

---

<sup>5</sup>We suspect smaller cities may potentially represent qualitatively different empirical setting, the inclusion of which might confound our estimates.

Table 1: Summary Statistics of 400 Markets over 36 Years

	Num. Obs.	Mean	Std. Dev.	Min	Max
<b>I. Number of Outlets</b>					
McDonald's	14,400	0.43	0.68	0	7
A&W	14,400	0.19	0.46	0	4
Harvey's	14,400	0.08	0.29	0	3
Burger King	14,400	0.14	0.37	0	2
Wendy's	14,400	0.08	0.27	0	2
Total of 5 Chains	14,400	0.93	1.18	0	9
<b>II. Market Characteristics</b>					
Population (thousand)	14,400	23.2	12.2	1.7	85.3
Income (thousand C\$)	14,400	52.3	17.1	17.4	194.5
Property Value (thousand C\$)	14,400	162.2	89.3	9.4	847.7

*Note:* The dollar values are expressed in the 2005 constant Canadian dollars.

*Source:* Archived phone directories (Yang 2012), Canadian Census.

### 2.3 Evidence of Non-monotonic Entry Strategy

Before we start developing and estimating a structural model, let us examine the patterns of entry/exit and its relationship with the concurrent market structure. Table 2 shows the five firms' choice probabilities conditional on the number of existing outlets of own and rival chains,  $N_i$  and  $N_{-i}$ .

Table 2: Entry/Exit and Market Structure

Probability of <i>Opening</i> an Outlet in a Given Year (%)				Probability of <i>Closing</i> an Outlet in a Given Year (%)			
$N_i$	$N_{-i}$ (Rival outlet)			$N_i$	$N_{-i}$ (Rival outlet)		
(Own outlet)	0	1	2+	(Own outlet)	0	1	2+
0	1.16	1.12	1.79	0	0	0	0
1	1.15	1.22	1.60	1	1.60	1.72	2.51
2+	0.73	4.24	2.13	2+	1.38	1.86	3.93

*Note:* Summary of the first-stage frequency estimates. See section 4.2 for details.

Two patterns emerge. First, the entry probability varies with market structure in a highly non-monotonic manner (left panel). That is, a firm is often more likely to open a new store when a few stores are already present, but such a positive correlation no longer holds when  $N_i \geq 2$  or  $N_{-i} \geq 2$ . Second, by contrast, the exit probabilities exhibit a simpler pattern, increasing with both  $N_i$  and  $N_{-i}$  most of the time (right panel). The higher exit rates in more contested markets suggest the force of competition, both between rival chains and within the same chain. A particularly high exit rate when  $(N_i, N_{-i}) = (2+, 2+)$  corroborates the anecdotal evidence that most markets cannot accommodate more than three shops, which is also consistent with the suspected racing behaviors in entry.

## 2.4 Preliminary Static Regressions

In the presence of these non-monotonic entry behaviors, a conventional static approach may yield puzzling results, such as a “positive effect of rivals’ presence” on profits. Let us examine the results from the following ordered probit regressions,

$$y_{it} = \begin{cases} \textit{exit} & \text{if } y_{it}^* \leq c_1 \\ \textit{unchanged} & \text{if } c_2 < y_{it}^* \leq c_3 \\ \textit{enter} & \text{if } c_3 < y_{it}^*, \end{cases}$$

where the latent profit,

$$y_{it}^* = \gamma_2 N_{it} + \gamma_3 N_{-it} + Z_t \theta + \varepsilon_{it},$$

incorporates the number of existing outlets, a vector of market characteristics, and the i.i.d. standard normal cost shocks.

Table 3: Preliminary Regressions (Ordered Probit)

Dep. var.: <i>Entry/exit</i>	All Years		1980s Subsample	
	(1)	(2)	(3)	(4)
Own competition ( $\gamma_2$ )	-.3054*** (.0243)	-.3154*** (.0243)	-.5491*** (.0614)	-.5476*** (.0614)
Rival competition ( $\gamma_3$ )	.0240** (.0110)	.0140 (.0112)	.0813*** (.0261)	.0830*** (.0262)
Control for market characteristics	No	Yes	No	Yes
Number of observations	70,000	70,000	20,000	20,000
Pseudo $R^2$	.0127	.0150	.0271	.0281

*Note:* For illustration purposes only. Standard errors are in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively.

Columns 1 and 2 of Table 3 suggest a negative correlation between entry and the presence of own shops (i.e.,  $\hat{\gamma}_2 < 0$ ) in the full sample (1970–2005), but the correlation between entry and the presence of rival shops turns out to be positive (i.e.,  $\hat{\gamma}_3 > 0$ ). Moreover, when we restrict the data to a particular time period, as is commonly done in the literature (e.g., Toivanen and Waterson 2005), the estimated “positive effect” of rival competition becomes even stronger. This finding is not surprising if we consider the non-monotonic patterns of entry in the data (c.f., Table 2) and the underlying data-generating process, in which the store-development officers may have engaged in a preemptive entry game.

### 3 Model

The goal of this paper is to empirically assess the effects of cannibalization and preemption on the evolution of market structure. Such assessment requires a dynamic oligopoly model of entry/exit with multi-product firms, because cannibalization is a multi-product phenomenon, and preemption is a forward-looking behavior, with endogenous changes in market structure.

Time is discrete with infinite horizon  $t = 1, 2, \dots, \infty$ . A fixed number of firms (chains) are denoted by  $i$ . In any year  $t$ , each firm may sell (operate)  $N_i = 0, 1, 2, \dots$  products (outlets) in a given market and decides whether to increase, decrease, or maintain the same number of products (outlets),  $a_{it} \in \{1, 0, -1\}$ .<sup>6</sup>

The timeline within each year  $t$  is as follows. First, each firm  $i$  observes the industry state  $(N_{it}, N_{-it}, Z_t)$ , where  $N_{-it}$  is the number of rival chains' outlets, and  $Z_t$  is the demand conditions and other exogenous market characteristics. It also observes its own private cost shock,  $\varepsilon_{it}$ , reflecting idiosyncratic informational and managerial conditions (i.i.d. across alternatives and firms, and over time following the type-1 extreme value distribution). Each firm forms rational expectations regarding the rivals' decisions,  $a_{-it} \equiv \{a_{jt}\}_{\forall j \neq i}$ , and makes its own decision  $a_{it}$  to maximize its expected present value (discounted at  $\beta < 1$ ).

Second, each firm earns the period profit as a function of its own decision as well as the industry state,

$$\Pi_{it}(a_{it}, N_{it}, N_{-it}, Z_t) = N_{it} \bar{\pi}_{it}(N_{it}, N_{-it}, Z_t; \alpha, \theta) - C(a_{it}) + \varepsilon(a_{it}), \quad (1)$$

where  $\bar{\pi}_{it}(\cdot)$  is the average product-level (outlet-level) profit parameterized by  $\alpha$  and  $\theta$  (see section 4.3 for its empirical specifications), and

$$C(a_{it}) = \kappa_+ I\{a_{it} = 1\} + \kappa_- I\{a_{it} = -1\} \quad (2)$$

is the sunk costs associated with increasing and reducing products (outlets), parameterized by  $\kappa_+$  and  $\kappa_-$ .

Third, the firms' dynamic decisions  $a_t \equiv \{a_{it}\}_{\forall i}$  are implemented, and the firm-level state evolves according to

$$N_{it+1} = N_{it} + a_{it}. \quad (3)$$

The market characteristics,  $Z_t$ , also evolve according to some first-order Markov process.

Let us denote the industry state  $(N_{it}, N_{-it}, Z_t)$  by  $S_t$ . The following Bellman equation

---

<sup>6</sup>We define the action set in this way because almost all observations (over 99% of data) exhibit at most one positive/negative change in  $N_i$  per year. In principle, we may allow for multiple entries and exits.

characterizes firm  $i$ 's dynamic optimization problem,

$$V_i(S_t|\sigma) = \max \Pi_{it}(\sigma, S_t, \varepsilon_{it}) + \beta E_\varepsilon [V_i(S_{t+1}|\sigma) | S_t], \quad (4)$$

where  $\sigma$  denotes the profile of Markov-perfect strategies. The Markov perfect equilibrium (MPE) profile  $\sigma$  is the set of strategies and beliefs that satisfies the following inequality:

$$V_i(S, \sigma) \geq V_i(S, \tilde{\sigma}_i, \sigma_{-i}) \quad (5)$$

for all  $i$  and all unilateral deviations  $\tilde{\sigma}_i \neq \sigma_i$ .

The structural parameters of this model (henceforth collectively denoted by  $\psi$ ) are the sunk costs ( $\kappa_{entry}$  and  $\kappa_{exit}$ ) and the period-profit parameters  $\alpha$  and  $\theta$ , which govern the relationship between profit, market structure, and market characteristics. The goal of the next section is to estimate these parameters.

## 4 Estimation

### 4.1 Approach

To estimate the structural parameters of our model, we employ the conditional choice probability (CCP) approach of Bajari, Benkard, and Levin (2007), because our model is a dynamic discrete game in a stationary environment and our dataset contains a sufficient number of geographical markets to implement such a data-intensive method. This approach proceeds in two stages. The first stage non-parametrically recovers the equilibrium strategies from data ( $\hat{\sigma}$ ), which the second stage uses to compute the expected payoffs,  $\bar{V}_i(S, \sigma; \psi)$ . The underlying idea is to find the values of the parameter vector  $\psi$  that would best rationalize the observed equilibrium strategies ( $\hat{\sigma}$ ) in the sense that  $\hat{\sigma}$  delivers higher expected payoffs  $\bar{V}_i(S, \hat{\sigma}; \psi)$  than any other  $\bar{V}_i(S, \tilde{\sigma}; \psi)$  based on deviating strategies  $\tilde{\sigma}$ : revealed preference.

Specifically, our first stage uses a frequency estimator with discretized states to recover the MPE strategies

$$\widehat{P}_i(a|S) = \frac{\sum_{itm} I\{S_{itm} = S, a_{itm} = a\}}{\sum_{itm} I\{S_{itm} = S\}}. \quad (6)$$

The CCP approach requires this procedure to be non-parametric. Fortunately, the state space of our model is sufficiently parsimonious to permit such an approach.

In the second stage of estimation, we use the estimated MPE strategy profile,  $\hat{\sigma}$ , to compute the simulated sequences of period profits into the distant future, and construct the

expected values

$$\bar{V}_i(S, \hat{\sigma}; \psi) = E \left[ \sum_{t=0}^{\infty} \beta^t \Pi(S_t, \varepsilon_t; \psi) \mid S, \hat{\sigma} \right], \quad (7)$$

where the expectation is over the evolution of states.<sup>7</sup> The construction of these expected values utilizes the first-stage  $\hat{\sigma}$ , because from the perspective of a given firm, the latter embodies the rivals' MPE strategies and hence its MPE beliefs (rational expectations) over the evolution of states.

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 (5) implies the following distance metric to be non-negative:

$$g(S; \psi) \equiv \bar{V}_i(S, \hat{\sigma}; \psi) - \bar{V}_i(S, \tilde{\sigma}_i, \hat{\sigma}_{-i}; \psi) \geq 0. \quad (8)$$

We compute  $\bar{V}_i(S, \tilde{\sigma}_i, \hat{\sigma}_{-i}; \psi)$  from  $B$  such deviations, denote each distance metric by  $g_b$ , and construct the objective function

$$Q(\psi) = \frac{1}{B} \sum_b (\min \{g_b(S; \psi), 0\})^2, \quad (9)$$

which we subsequently minimize to obtain our estimates,  $\hat{\psi}$ .<sup>8</sup>

## 4.2 First Stage: Strategies and Beliefs

Table 2 in section 2.3 summarizes our first-stage estimates of the entry/exit strategy and belief, which exhibit highly non-monotonic choice probabilities with respect to market structure. Specifically, we construct these estimates by first discretizing the state space as follows: three bins for each of  $N_{it}$  and  $N_{-it}$ ,  $\{0, 1, 2\}$ , and two bins for each of  $(z_{1t}, z_{2t}, z_{3t})$ ,  $\{1, 2\}$ . The resulting 72 bins span the discretized state space, for each of which we obtain frequency estimates of entry/exit probabilities, as well as the transition matrix of the exogenous state variables  $(z_{1t}, z_{2t}, z_{3t})$ .<sup>9</sup>

## 4.3 Second Stage: Profits and Sunk Costs

Our main empirical challenge is to recover a reasonable economic relationship between profits and market structure in the presence of highly non-monotonic entry/exit behaviors in data

<sup>7</sup>For each market, we run 1,000 simulations over 36 years to compute the expected values.

<sup>8</sup>We generate 1,000 perturbed policies by adding random draws from  $N(0, 0.01)$  to the estimated conditional choice probabilities of entry and exit in each state.

<sup>9</sup>We prefer this coarse grid because it avoids empty bins when applied to the data. In unreported results, we also tried finer grids (with some extrapolation to fill in empty bins) and obtained similar second-stage estimates.

Table 4: Second-Stage Estimates

	Estimate	Standard Error
<b>Competition</b>		
Base profit ( $\alpha_1$ )	-0.0191	0.0003
Own competition ( $\alpha_2$ )	-0.0110	0.0003
Rival competition ( $\alpha_3$ )	-0.0023	0.0001
<b>Market Characteristics</b>		
Population ( $\theta_1$ )	0.0020	0.0001
Average income ( $\theta_2$ )	0.0083	0.0001
Commercial property value ( $\theta_3$ )	0.0109	0.0001
<b>Sunk Costs</b>		
Entry sunk cost ( $\kappa_+$ )	-0.0323	0.0003
Exit sunk cost ( $\kappa_-$ ): Normalized	0	-

*Note:* Standard errors are from bootstrapping across markets.

(as evidenced by our descriptive statistics and non-parametric estimates in sections 2.3 and 4.2). For this purpose, we follow the standard empirical models (e.g., Seim 2006) and specify the average period profit per product (outlet) as

$$\bar{\pi}_{it}(N_{it}, N_{-it}, Z_t; \alpha, \theta) = \alpha_1 + \alpha_2 N_{it} + \alpha_3 N_{-it} + \theta_1 z_{1t} + \theta_2 z_{2t} + \theta_3 z_{3t}, \quad (10)$$

where  $\alpha_1$ ,  $\alpha_2$ , and  $\alpha_3$  represent the base profit, competition with same-chain outlets, and competition with rival-chain outlets, respectively. The  $z$ s and  $\theta$ s denote market characteristics (population, household income, and commercial property value) and their impacts on profits.

Table 4 shows the second-stage estimates of the profit function and sunk costs, and contains three findings. First, 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.,  $|\hat{\alpha}_2| > |\hat{\alpha}_3|$ ), making cannibalization the single most important determinant of profits. The negative effect of rival-chain shops (i.e.,  $\hat{\alpha}_3 < 0$ ) is reasonable and unsurprising, but this effect is something the existing literature often struggled to find using a static approach (e.g., Toivanen and Waterson 2005). Hence this result may suggest the appeal of fully dynamic approaches in the presence of preemptive behaviors that generate positively correlated entries of rivals.

Second, all three market characteristics affect profits positively (i.e.,  $\hat{\theta}_1 > 0$ ,  $\hat{\theta}_2 > 0$ , and  $\hat{\theta}_3 > 0$ ). Population and income are demand shifters, so their positive impacts do not surprise. By contrast, commercial property value deserves further attention because, taken literally, it should be a cost shifter. However, it may also reflect unobserved attractiveness of a location such as daytime consumer traffic. Therefore, we are inclined to interpret a

positive  $\hat{\theta}_3$  as reflecting the net desirability of running a fastfood business in a commercially active area, helping us control for potential heterogeneity across locations.

Third, 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 not separately identified from each other. Under our normalization,  $\hat{\kappa}_- = 0$ , Aguirregabiria and Suzuki (2012) 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. We will pay attention to this non-identification issue when we construct and interpret our counterfactual simulations in the next section.

## 5 Effects of Preemption and Cannibalization on Entry

### 5.1 Ronald McDonald against the Machines

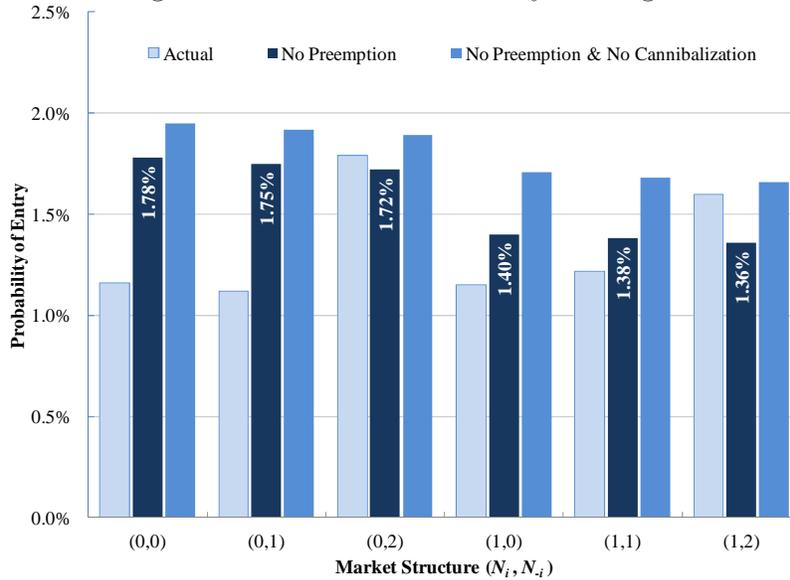
We assess the roles of preemption and cannibalization in entry decision by comparing the actual entry strategy with those under hypothetical settings in which preemptive motives and cannibalization are muted. We first operationalize the no-preemption environment by focusing on McDonald’s entry strategy and making its rivals non-strategic players who enter and exit at exogenous rates irrespective of  $N_{mcd}$ . Then we implement the no-cannibalization setting by altering the firm’s profit function such that its shops compete with each other as if they belonged to different brands (i.e.,  $\tilde{\alpha}_2 = \hat{\alpha}_3$ ).

### 5.2 No-Preemption Counterfactual

In the no-preemption counterfactual, McDonald’s four rivals enter and exit with their observed choice probabilities in the data, conditional on  $N_{-mcd}$  and  $Z$  but not on  $N_{mcd}$ . In other words, they become part of “nature” from the perspective of McDonald’s, which solves what has effectively become a single-agent dynamic programming problem. McDonald’s cannot influence its rivals, but the latter’s presence will hurt the former’s profits. Thus this counterfactual purely isolates McDonald’s preemptive motives while preserving the possibility of McDonald’s being preempted by its rivals.

Figure 2 (dark bars) shows that without preemptive motives, the entry probability of McDonald’s monotonically decreases with both  $N_{mcd}$  and  $N_{-mcd}$ . Its comparison with the observed policy in the data (light bars) highlights the latter’s non-monotonicity and suggests

Figure 2: Counterfactual Entry Strategies



*Note:* The counterfactuals are based on the re-normalization of  $\tilde{\kappa}_-$  at 40, and hence are not directly comparable with the actual probabilities in terms of levels. However, the main results concerning monotonicity and flatness are not sensitive to calibration (see next section).

the optimal entry strategy becomes highly non-monotonic in dynamic oligopoly.<sup>10</sup> Finally, the negative impact of  $N_{mcd}$  is more pronounced than that of  $N_{-mcd}$  because of cannibalization, which is consistent with our estimation results in the previous section (i.e.,  $|\hat{\alpha}_2| > |\hat{\alpha}_3|$ ).

### 5.3 No-Cannibalization Counterfactual

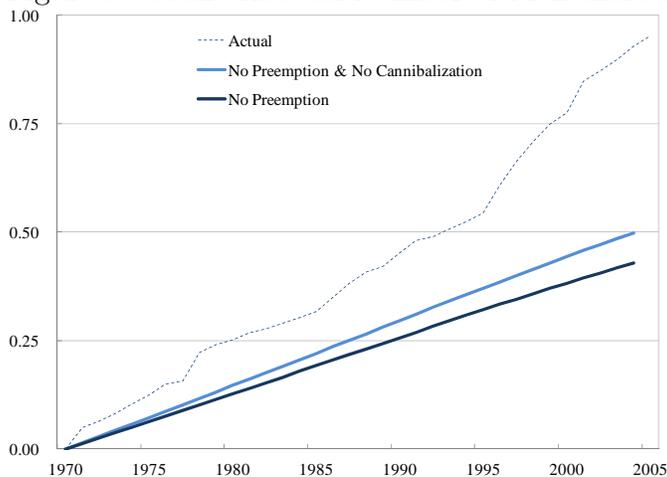
Let us now analyze the impact of cannibalization. In addition to shutting down preemptive motives, we mute cannibalization concerns to assess their impact on entry, by setting  $\tilde{\alpha}_2 = \hat{\alpha}_3$ .<sup>11</sup> Figure 2 (medium-colored bars) shows McDonald’s would enter more aggressively without cannibalization (i.e., the medium-colored bars are higher than the dark bars across the board), and its entry strategy becomes less sensitive to its existing shops (i.e., the entry probabilities are more “flat” between  $N_i = 0$  and 1). These results are consistent with our estimate of cannibalization as the most important determinant of profit.

Figure 3 plots  $\{\tilde{N}_t^{mcd}\}_t$  in the two counterfactuals and highlights the importance of cannibalization to the evolution of market structure. Without cannibalization, McDonald’s would expand 16% faster during the sample period, relative to the no-preemption counterfactual. One practical interpretation of this no-cannibalization counterfactual may be to consider

<sup>10</sup>This finding cautions against imposing monotonic functional forms in the first stage.

<sup>11</sup>We may alternatively consider muting cannibalization but not preemption. However, such a counterfactual requires a full solution of some dynamic game, which may or may not be consistent with the one we estimated using a two-step approach.

Figure 3: Counterfactual Number of McDonald's



*Note:* Mean of 400 markets, with 1,000 simulations for each market. The counterfactuals are based on the re-normalization of  $\tilde{\kappa}_-$  at 40, and hence are not directly comparable with the actual probabilities in terms of levels. However, the main results concerning monotonicity and flatness are not sensitive to calibration (see next section).

product (outlet) differentiation within the same chain, such as multi-brand operation. A multi-brand firm can potentially benefit from less cannibalization among its products or outlets while maintaining the ability to preempt the product space just as effectively as single-brand multi-product firms. Such a dynamic and strategic advantage may explain the proliferation of multi-brand operations and multi-chain mergers, even in the absence of more traditional reasons such as scale or scope economies. A full examination of this theoretical possibility is beyond the scope of this paper, but it might suggest potentially fruitful avenues to explore with dynamic oligopoly frameworks.

## 6 Robustness and Sensitivity

### 6.1 Robustness Checks for Unobserved Market Characteristics

This section shows the key feature of our estimation results (i.e.,  $\hat{\alpha}_2 < \hat{\alpha}_3 < 0$ ) holds across different subsamples, which we interpret as suggestive of the robustness of our findings with respect to the possibilities of unobserved market characteristics. Specifically, we conduct re-estimation by subsample according to four different criteria, each of which represents a potential source of unobserved heterogeneity.<sup>12</sup>

<sup>12</sup>Due to smaller sample sizes, the re-estimates in this section tend to feature some empty bins in the first-stage choice probability estimates, which we simply replace with zeros. The sole purpose of this section is to assess the extent to which our main findings hold.

Table 5: Estimates by Subsample

	(A) By Retail Sales Quartile				(B) By Peak $N_t$	
	1st	2nd	3rd	4th	$\leq 4$	$> 4$
Base profit ( $\alpha_1$ )	0.0068	0.0168	0.0324	0.0463	-0.0074	0.0761
Own competition ( $\alpha_2$ )	-0.0036	-0.0280	-0.0089	-0.0506	-0.0207	-0.0208
Rival competition ( $\alpha_3$ )	-0.0024	-0.0099	-0.0027	-0.0026	-0.0070	-0.0016
Population ( $\theta_1$ )	-0.0018	-0.0071	0.0024	0.0125	0.0011	-0.0094
Average income ( $\theta_2$ )	-0.0023	0.0313	0.0115	0.0138	0.0107	0.0342
Commercial property value ( $\theta_3$ )	0.0102	0.0121	0.0110	0.0044	0.0137	0.0006
Entry sunk cost ( $\kappa_+$ )	0.0663	0.2440	-0.0671	0.2573	0.0206	0.5444
Exit sunk cost ( $\kappa_-$ ): Normalized	0	0	0	0	0	0
	(C) By City				(D) By Time Period	
	Toronto	Montreal	Vancouver	Other 4	1970–88	1988–2005
Base profit ( $\alpha_1$ )	0.0440	-0.03663	0.1077	0.0110	0.0327	0.0196
Own competition ( $\alpha_2$ )	-0.0401	-0.0071	-0.0299	-0.0230	-0.0144	-0.0031
Rival competition ( $\alpha_3$ )	-0.0075	-0.0020	-0.0155	-0.0015	-0.0013	-0.0022
Population ( $\theta_1$ )	-0.0008	0.0070	-0.0207	0.0104	-0.0044	-0.0025
Average income ( $\theta_2$ )	0.0154	0.0115	0.0423	-0.0160	-0.0223	-0.0003
Commercial property value ( $\theta_3$ )	0.0021	0.0157	0.0082	0.0252	0.0069	-0.0025
Entry sunk cost ( $\kappa_+$ )	0.1600	0.0171	0.8132	0.1037	-0.0359	0.0193
Exit sunk cost ( $\kappa_-$ ): Normalized	0	0	0	0	0	0

Note: Second-stage coefficient estimates.

First, our data do not contain non-hamburger activities, which raises concerns over omitted variable biases. We address this issue by splitting the sample of 400 markets into four groups based on the retail sales pertaining to food and restaurant businesses in 2003. Panel A of Table 5 shows  $\hat{\alpha}_2 < \hat{\alpha}_3 < 0$  in all subsamples, highlighting the stability of our findings concerning cannibalization and preemption.

Second, 25 markets in our data contain more than four outlets at some point during the sample period. This number is a small fraction of the data but deserves additional scrutiny because our model’s state space treats all cases with  $(N_{it}, N_{-it}) = (2+, 2+)$  equally. Moreover, these markets might represent fundamentally different neighborhoods with sudden economic booms that attracted multiple entrants, thereby generating an appearance of preemptive entry. Panel B investigates this possibility and finds similar results across subsamples. The cannibalization estimates ( $\hat{\alpha}_2$ ) are almost identical between these 25 markets and the other 375 markets, whereas the inter-chain competition ( $\hat{\alpha}_3$ ) seems attenuated in those 25 “booming” markets, presumably because our estimation approach interprets the coexistence of many shops in this subsample as evidence of less competition.<sup>13</sup>

<sup>13</sup>We are currently investigating the possibility of incorporating such unobserved market heterogeneity more explicitly. See the final paragraph of section 7 for a brief discussion.

Third, our baseline estimates ignore city-specific factors such as urban development, traffic patterns, local ordinances, politics, climate, or ethnic composition. To explore how our estimates vary across cities, Panel C splits the sample into Toronto, Montreal, Vancouver, and the other four cities, and finds some idiosyncrasy. However, the main pattern (i.e.,  $\hat{\alpha}_2 < \hat{\alpha}_3 < 0$ ) still holds.

Finally, Panel D splits the data in the time dimension to assess the possibility that the fundamental economics of hamburger shops changed over decades. The results suggest it could, but the main pattern persists.

## 6.2 Sensitivity Analysis of No-Preemption Counterfactual

This section shows our main results from the no-preemption counterfactual are not sensitive to the way we re-normalize the sunk cost of exit,  $\tilde{\kappa}_-$ . As we discussed in section 4.3, our class of dynamic entry game contains three dynamic parameters that are typically not separately identified. The normalization of  $\kappa_- = 0$  is a usual approach, but the solution of McDonald’s counterfactual problem may not appear entirely reasonable unless we re-normalize  $\tilde{\kappa}_-$  (and consequently  $\tilde{\kappa}_+$  and  $\tilde{\alpha}_1$  as well). This step is necessary because a zero exit cost will imply exceedingly high probabilities of entry/exit, as Table 6 shows (row 1, with  $\tilde{\kappa}_- = 0$ ).

Table 6: Sensitivity of Counterfactual to Re-normalization

Calibrated value of $\tilde{\kappa}_-$	Entry Strategy in No-Preemption Counterfactual						
	Conditional Probability			Odds Ratio			
	Pr (+)	Pr (+  $N_i = 0$ )	Pr (+  $N_{-i} = 0$ )	$\frac{\text{Pr}(+ N_i=1)}{\text{Pr}(+ N_i=0)}$	$\frac{\text{Pr}(+ N_i=2)}{\text{Pr}(+ N_i=0)}$	$\frac{\text{Pr}(+ N_{-i}=1)}{\text{Pr}(+ N_{-i}=0)}$	$\frac{\text{Pr}(+ N_{-i}=2)}{\text{Pr}(+ N_{-i}=0)}$
0	46.68%	62.40%	46.76%	.6749	.5692	.9982	.9964
20	5.15%	9.28%	5.20%	.6630	.0000	.9889	.9784
40	1.04%	1.75%	1.06%	.7858	.0000	.9852	.9714
60	0.15%	0.25%	0.15%	.8503	.0000	.9842	.9697
80	0.02%	0.03%	0.02%	.8625	.0000	.9841	.9695
Actual	1.68%	1.36%	1.01%	.9730	1.7402	2.1716	1.8218

Note: The baseline counterfactuals in section 5 are based on  $\tilde{\kappa}_- = 40$ .

A comparison of counterfactual entry strategies across different parameterizations in Table 5 (for  $\tilde{\kappa}_- = 0, 20, 40, 60, 80$ ) indicates the *levels* of entry probabilities (columns 1 through 3) depend on our choice of  $\tilde{\kappa}_-$ , but the odds *ratios* do not (columns 4 through 7). That is,  $\tilde{\kappa}_-$  does not affect our main conclusion that the absence of preemptive motives leads to the optimal entry probabilities that are monotonically decreasing in  $N_i$  and  $N_{-i}$ .<sup>14</sup>

<sup>14</sup>The case of  $\tilde{\kappa}_- = 0$  is a possible exception because frictionless entry/exit incentivizes firms to “enter” even when they already operate the maximum number of shops (i.e.,  $N_i = 2$ ) for the sole purpose of earning

We still prefer  $\tilde{\kappa}_- = 40$  for our baseline counterfactuals, but only because it generates the levels of entry probabilities that are roughly comparable to the data. Finally, we do not separately discuss the sensitivity of the no-cannibalization counterfactual, because it builds on the no-preemption counterfactuals and hence inherits the same sensitivity properties as in Table 6.

## 7 Conclusion

We extend the dynamic entry framework to incorporate multi-product firms, and empirically assess the effects of preemption and cannibalization on entry. The estimated entry strategy is highly non-monotonic in concurrent market structure and suggests racing behaviors that are consistent with anecdotal evidence. By contrast, our no-preemption counterfactual exhibits the optimal entry probability that is monotonically decreasing in the number of competing shops. Hence the results highlight the importance of accounting for dynamic strategic incentives in analyzing market structure. Our comparison of dynamic and static estimates seems to caution against imposing the “long-run equilibrium” assumptions that are inherent in static frameworks, because markets may take decades to reach one.

We also investigate the impact of cannibalization, which turns out to be the single most important determinant of period profit. Consequently, our no-cannibalization counterfactual features the optimal entry probability that is much less sensitive to the number of own outlets. These results seem to suggest the potential benefits of product differentiation, because a multi-brand operation may ameliorate cannibalization concerns while retaining the ability to preempt rivals by saturating the market with multiple products. Such possibilities would deserve further investigations from both private and public perspectives.

We are currently assessing the possibility of incorporating unobservably heterogeneous markets at the model/estimation level, in a more systematic way than a series of robustness checks. As we discussed in section 6.1, markets might be heterogeneous in some unobservable manners, which could potentially explain some of the correlated entry behaviors of firms. We are investigating the applicability of recently developed empirical methodologies to our context. If applicable, we expect such augmented frameworks to strengthen our current findings (i.e.,  $\hat{\alpha}_2 < \hat{\alpha}_3 < 0$ ). Specifically, we expect the magnitude of  $\hat{\alpha}_3$  to increase, once we allow for unobservably heterogeneous markets.

---

some lucky draws of  $\varepsilon(a_{it} = 1)$ . We dismiss this special result as a purely mathematical artifact rather than an economically meaningful outcome.

## References

- [1] Aguirregabiria, Victor, and Junichi Suzuki. 2012. “Identification and Counterfactuals in Dynamic Models of Market Entry and Exit.” Manuscript, University of Toronto.
- [2] Arcidiacono, Peter, and Robert A. Miller. 2011. “Conditional Choice Probability Estimation of Dynamic Discrete Choice Models with Unobserved Heterogeneity.” *Econometrica*, 79(6): 1823–67.
- [3] Bajari, P., L. Benkard, and J. Levin. 2007. “Estimating Dynamic Models of Imperfect Competition.” *Econometrica*, 75: 1331–70.
- [4] Berry, Steven. 1992. “Estimation of a Model of Entry in the Airline Industry.” *Econometrica*, 60(4): 889–917.
- [5] Bresnahan, Timothy F., and Peter C. Reiss. 1991. “Entry and Competition in Concentrated Markets.” *Journal of Political Economy*, 99(5): 977–1009.
- [6] Collard-Wexler, Allan. 2013. “Demand Fluctuations in the Ready-Mix Concrete Industry.” *Econometrica*, 81(3): 1003–37.
- [7] Kasahara, Hiroyuki, and Katsumi Shimotsu. 2009. “Nonparametric Identification of Finite Mixture Models of Dynamic Discrete Choices.” *Econometrica*, 77(1): 135–75.
- [8] Love, John. 1995. *McDonald’s: Behind the Arches*. Bantam Books: New York.
- [9] Mazzeo, M. J.. 2002. “Product choice and oligopoly market structure.” *RAND Journal of Economics*, 33(2): 221–42.
- [10] Ryan, Stephen P.. 2012. “The Costs of Environmental Regulation in a Concentrated Industry.” *Econometrica*, 80(3): 1019–61.
- [11] Seim, Katja. 2006. “An empirical model of firm entry with endogenous product-type choices.” *RAND Journal of Economics*, 37.
- [12] Thomadsen, Raphael. 2005. “The effect of ownership structure on prices in geographically differentiated industries.” *RAND Journal of Economics*, 36(4): 908–29.
- [13] Toivanen, O. and M. Waterson. 2005. “Market structure and entry: where’s the beef?” *RAND Journal of Economics*, 36.
- [14] Yang, Nathan. 2012. “March of the Chains: Herding in Restaurant Locations.” NET Institute working paper.