Measuring Deterrence Motives in Dynamic Oligopoly Games*

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Abstract

This paper presents a new decomposition approach for measuring deterrence motives in dynamic oligopoly games. Our approach yields a scale-free and interpretable measure of deterrence motives that informs researchers about the proportion for which deterrence motives account of all entry motives. We illustrate the use of our new approach by conducting an empirical case study about the dynamics of coffee chain stores in Toronto, Canada from 1989 to 2005. Under this empirical context, our measure of deterrence motives, quantified based on the estimates of structural primitives, suggests that a noticeable proportion of entry motives can be attributed to deterrence, and is as high as 32% for the increasingly dominant coffee chain Starbucks in certain types of markets. In summary, the empirical study demonstrates that our method has the capabilities to establish the "who" and "when" dimensions of deterrence.

Keywords: Chain Stores; Dynamic Oligopoly Games; Entry and Exit; Dynamic Discrete Choice; Industry Dynamics; Market Power; Preemption; Retail Strategy

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1 Introduction

In almost all industries, firms face the decision of when to enter markets or expand. Entering early or expanding quickly before demand takes off risks slow recovery of the initial investment, but late entry may not be worthwhile at all if the market has been saturated by entry of other firms. This trade-off in entry timing sometimes induces firms to enter a market and add stores early so as to deter the entry of rivals (Shen and Villas-Boas, 2010). In the retail industry, for example, entry deterrence has emerged as one potential driver of aggressive entry and expansion, and these patterns have been discussed in media, as pointed out in *The Economist* (2014):

> The modern high street can give an overwhelming sense of deja vu. Fans trundling to the football stadium of Tottenham Hotspur, a team from north London, pass six William Hill bookmakers on the main approach. Tourists traipsing along a half-mile stretch of 23rd Street in New York pass five Starbucks outlets. In Tokyo, 7-Eleven boasts 15 stores within a similar distance of Shinjuku station.

It is often speculated that this expansionary behavior is driven by deterrence motives, and thus, this type of firm entry behavior has been of interest to antitrust practitioners. For example, in the late 1970s, the U.S. Federal Trade Commission (FTC) charged breakfast cereal companies Kellogg's, General Mills, and General Foods with deterrence via the introduction of about 150 new brands during the period of 1950-1970 (Viscusi et al., 2005). More recently, in March 2014, the Israel parliament passed the Law for Encouragement of Competitiveness in the Food Sector, which prevents a large wholesaler from opening a second big store in a pre-defined "competitive geographic area" (Library of Congress, 2014). In light of anecdotal patterns of rapid market expansion, an important question for both academics and practitioners to answer is whether deterrence motives are driving (smaller) firms out of the market. Furthermore, it might be important to establish the degree of heterogeneity in these deterrence motives across firms and markets, if policy makers and managers wish to obtain more targeted insights (i.e., the "who" and "when" behind deterrence).

At the foundation of answering these questions is the identification of deterrence motives. Unfortunately, identifying these motives empirically is inherently difficult, as labeling behavior as being deterrence-motivated often requires a clear (and beyond speculative) understanding of the future option value of keeping competitors out of the market (e.g., US Department of Justice, 2008). To assess this option value, the fundamental challenge is that it involves disentangling confounding forces. For example, suppose that a firm enters today, and that its incumbency status will become observable to rivals tomorrow. If it commits to staying in the market, its rivals would hesitate to enter the market tomorrow. Anticipating that, the firm will enter aggressively today, investing more capital. This deterrence (i.e., "indirect") effect is different from the more immediate (i.e., "direct") effect of competition, which is the outcome when a firm takes its rivals' anticipated actions as given rather than as responses to the firm's own decisions. Both of these effects co-exist in a dynamic oligopoly game, and they often interact with one another, thereby confounding their individual roles. To address this methodological challenge, we propose a novel decomposition approach that is derived theoretically under the context of dynamic oligopoly competition (Section 2). These decompositions are then used to partition various confounding benefits from entry (Section 3). The key output from our methodology is the proportion to which deterrence motives account for all entry motives.

With this new framework in place, we demonstrate how our framework can be applied to an empirical setting. We conduct a case study about coffee chain industry dynamics in Toronto, Canada from 1989 to 2005 (Section 4). The empirical analysis aims to answer two questions of substantive interest. First, to what extent do deterrence motives drive the industry dynamic patterns in the the coffee chain industry? Second, is there heterogeneity in the intensity of these motives across firms and markets? This unique coffee chain data allows us to estimate a dynamic game of entry and exit, and the model primitives are ultimately used to quantify each firm's intrinsic deterrence motives.

The calculated measure confirms the existence of deterrence motives in our coffee chain empirical setting, and that these motives are noticeably asymmetric across the firms and market types. In particular, we confirm that the increasingly dominant chain, Starbucks, exhibits the strongest motivation to deter entry; we find that deterrence motives account for 9% of all entry motives for Starbucks. Furthermore, we show that its deterrence motives are not uniform across different types of markets (ranges from 0% to 32%). These empirical insights suggest that our deterrence measure has the capability to distinguish between cases of retail outlet expansion (in a certain type of market) that may or may not be of concern to antitrust authorities. In other words, our new framework offers antitrust officials and managers the opportunity to not only detect the existence of deterrence motives as past literature has almost exclusively focused on, but to also pinpoint the "who" and "when" dimensions of deterrence. Ultimately, our framework can help assess the extent to which deterrence motives might be driving increasingly some firms (e.g., Starbucks) to push out their competitors (e.g., Country Style). In summary, this paper aims contribute towards this broader discussion by bringing forward an empirically-relevant, parsimonious and general framework to measure deterrence motives in dynamic games and being able to fully characterize deterrence motives in this manner can help facilitate new research opportunities for academics (Section 5).

1.1 Related Literature

Our decomposition approach is inspired by the theoretical contributions of Besanko et al. (2014, 2019), where they propose "sacrifice" tests to detect predatory pricing. This past work is important, as they demonstrate that equilibrium pricing conditions can be broken down into different components analytically. Analogous to them, we apply a similar strategy to decompose the equilibrium entry and expansion decisions in order to characterize various motivations behind entry. More generally, Besanko et al. (2014, 2019) demonstrate the informativeness of the analytical structure of equilibrium conditions. In our paper, we demonstrate the power of these decompositions to a large and more general class of models for dynamic oligopoly games, and most importantly, show how these decompositions can provide data-driven insights.

Based on the past empirical literature that aims to detect deterrence motives, a commonly used strategy involves counterfactual design (e.g., Aguirregabiria and Ho, 2012; Igami, 2017; Igami and Yang, 2016; Zheng, 2016; Hünermund et al., 2014). Existing alternative methods differ from one another primarily via the underlying implementation assumptions they need to make about how exactly to shut-off deterrence motives. These implementation approaches can be grouped into four broad categories. The first approach involves limiting preemption by changing the structural primitives of the model, thereby reducing the incumbent firm's ability to commit. A second approach is to eliminate preemptive motives for one firm by making its competitors ignore its presence in the market. A third category aims to capture a lower bound to preemption by having one firm disregard its competitor's potential entry for one future period. Finally, the fourth type uses an open-loop equilibrium to remove preemption in the counterfactual world, in which the open-loop equilibrium makes firms pre-commit to a series of actions for every period in the future at the beginning of time and the strategies are chosen to maximize firms' values at the initial state. Despite these important innovations, there is no consensus as to which implementation approach should be most preferred.

Our framework makes two important points of departure from this literature. The first point of departure is methodological, as our decomposition approach allows the researcher to avoid making discretionary judgment calls about how exactly a counterfactual scenario is operationalized; in some sense, our approach reduces the degrees of freedom a researcher might have regarding implementation design, and thus, the assumptions needed for the model and subsequent post-estimation analysis are essentially the same. More specifically, we can avoid the potentially fraught choice about which of the four broad approaches we use to implement the off-equilibrium counterfactual scenario that "shuts off" deterrence motives. Even if researchers were to agree on the proper way to implement the counterfactual scenario, the fact that commonly used models require some type of normalizations (e.g., those involving exit, entry, and operational costs) imply that the counterfactual outcomes might at best be partially identified (e.g., Kalouptsidi et al., 2021). A parallel benefit from avoiding these assumptions about counterfactual implementation is that the proportion to which deterrence motives account for all entry motives might be easier to interpret across firms and markets as it is scale-free (i.e., a percentage). Thus, the second point of departure for our framework is substantive since our deterrence measure not only detects the existence of deterrence motives, but also the intensity via the quantified proportion. Our empirical case study demonstrates that the heterogeneity in the intensity of deterrence motives across firms and markets can provide policy makers and managers targeted insights about the threats of deterrence-motivated entry (i.e., identifying the firms that are likely to have the strongest motive, and in which type of markets).

More generally, our model framework contributes to the older theoretical literature about deterrence that have largely relied on stylized models. These older models have emphasized the importance of strategic commitment. For example, two-period models in Schmalensee (1978) and Eaton and Lipsey (1979) assume irreversible entry, which enables firms to fully commit to staying in the market after entry; thus, preemption is always successful in this setting. Schmalensee (1978) illustrates this in the context of the breakfast cereal industry, and Eaton and Lipsey (1979) prove this theory for a growing market. Other examples of theoretical papers on entry deterrence include Gilbert and Newberry (1982), Gilbert and Harris (1984), Fudenberg and Tirole (1985) and Bonanno (1987). These theoretical findings were later challenged by Judd (1985), who pointed out that if exit is possible, the incumbent cannot preempt entry without a large exit cost because the substitution effect between product locations can induce the incumbent to exit once challenged by the entrant. Subsequent theoretical literature focuses on establishing the role of large exit costs. On a similar note, Hadfield (1991), shows that the renegotiation of franchise contracts can be very costly for an incumbent franchisor if it decides to close a store, while Choi and Scarpa (1992), illustrates that withdrawing a product can damage a brand's reputation and reduce sales of other products under the same brand. To complement this existing literature, our approach is relevant for a large class of dynamic oligopoly games, and thus, we are able to offer data-driven insights about the underlying theoretical mechanisms behind aggressive entry.

2 Model

Our theoretical framework follows the seminal work of Erickson and Pakes (1995), in order to model forward-looking firms that repeatedly interact over a long-period of time. Compared to earlier stylized models of entry deterrence, such as Schmalensee (1978), Eaton and Lipsey (1979) and Judd (1985), our modeling allows firms to engage in ongoing entry and exit opportunities, a feature that has crucial implications for evaluating preemption (Judd, 1985). In principle, our analytical framework is general enough to be applied to patterns of industry dynamics that are observed in data, unlike previously developed analytical models of entry (Doraszelski and Pakes, 2007). We demonstrate how our framework can be applied to actual data about industry dynamics in Section 4.

We focus on the dynamic strategic interactions between N retail chains. They sell differentiated but substitutable products and compete in two dimensions: (1) a dynamic dimension where firms choose to add or contract the number of stores in a market, and (2) a static dimension where firms set prices or quantities by taking market structure, demand and costs as given. They have a discount factor of $\beta \in (0, 1)$ and aim to maximize their long-run discounted payoffs in an infinite horizon game. Although the general setting in which we set up the model and derive the decomposition is a retail setting, the model and the decomposition are general enough to accommodate other types of models where investment decision is the core strategic action; for example, the quality-ladder model in Pakes and McGuire (1994). We discuss how our model and decomposition can be applied to that setting at the end of this section as well as Section 3.

Firms and states Firm $i \in \{1, 2, \ldots, N\}$ is described by its state $s_i = (n_i, z)$, where $n_i \in \{0, 1, \ldots, M\}$ is the number of stores that firm i has in the market. z is an exogenous state variable that describes the market demand and cost conditions that are common to all firms, and it follows a Markov stochastic process. $n_i = 0$ identifies firm i as being inactive in a market. We use the vector $\boldsymbol{s} = (\boldsymbol{n}, z) = (n_1, \ldots, n_N, z)$ to describe all firms' states. In the text that follows, we use the subscript $-i$ to denote all firms in the market other than i.

At the beginning of each period, firms compete in the product market by taking the state $\boldsymbol{s}$

as given. Then firms simultaneously make decisions on adding or closing a store or do nothing. They immediately incur an entry cost by adding a store and receives a scrap value by closing a store; however, their states do not change until the beginning of the next period because building or closing a store takes one period of time to realize.

Actions and payoffs The action of firm i is denoted by $a_i \in \mathcal{A} \equiv \{-1, 0, 1\}$, with -1 indicating closing a store, 0 doing nothing, and 1 adding a store. $\mathcal{A}$ is the action space. Firm i's action affects only n_i, but not z. The transition of n_i from now to the next period is $n_i' = n_i + a_i$. In this paper, we use one apostrophe $'$ to denote the next period and double apostrophes $''$ to denote two periods from now.

Every time firm i adds a store, it incurs an entry cost of $\hat{\kappa}_i^+(s_i)$, which includes expenses setting up the outlet, and every time it closes a store, it receives the scrap value $\hat{\kappa}_i^-(s_i)$ that comes from liquidation of the assets at an outlet. Both $\hat{\kappa}_i^+(s_i)$ and $\hat{\kappa}_i^-(s_i)$ are functions of firm i's state s_i. Following the equilibrium purification practice in dynamic games (e.g., Doraszelski and Satterthwaite, 2010; Ryan, 2012; Aguirregabiria and Mira, 2007), we assume that there is a random shock in the entry cost and scrap value, such that $\hat{\kappa}_i^+(s_i) = \kappa_i^+(s_i) + \varepsilon_i(a_i = 1)$ and $\hat{\kappa}_i^-(s_i) = \kappa_i^-(s_i) + \varepsilon_i(a_i = -1)$. In addition, if firm i does nothing, it receives a shock $\varepsilon_i(a_i = 0)$ to its fixed cost. $\boldsymbol{\varepsilon_i}$ is known only to firm i, and it is i.i.d. across actions, time and firms.

Firms receive a profit from product competition. Let $\pi_i(\boldsymbol{n}, z)$ denote the profit for firm i. Taking into account of the cost of actions, we can write firm i's per-period flow payoff as

$$\Pi_i(a_i, \boldsymbol{n}, z, \varepsilon_i) \equiv \pi_i(\boldsymbol{n}, z) + C_i(a_i, n_i, z) + \varepsilon_i(a_i) \tag{1}$$

where $C_i(\cdot) = -\mathbb{1}(a_i > 0)\kappa_i^+(s_i) + \mathbb{1}(a_i < 0)\kappa_i^-(s_i)$.

Markov Perfect Equilibrium We assume that firms play stationary Markov strategies, and the equilibrium concept is a Markov Perfect Equilibrium (MPE). Let $\sigma = (\sigma_i(\boldsymbol{s}, \varepsilon), \sigma_{-i}(\boldsymbol{s}, \varepsilon))$ define the strategy functions for the N firms. Firms choose their strategies to maximize the following Bellman equation:

$$\tilde{V}_i(\boldsymbol{s}, \varepsilon, \sigma) = \Pi_i(\boldsymbol{s}, \varepsilon, \sigma(\boldsymbol{s}, \varepsilon)) + \beta \mathbb{E}\left[\tilde{V}_i(\boldsymbol{s'}, \varepsilon', \sigma)|\boldsymbol{s}, \varepsilon, \sigma(\boldsymbol{s}, \varepsilon)\right]. \tag{2}$$

In an MPE, the strategy profile σ satisfies the following condition for all firms at all states:

$$\tilde{V}_i(\boldsymbol{s}, \varepsilon, \sigma|\sigma_i^*, \sigma_{-i}^*) \geq \tilde{V}_i(\boldsymbol{s}, \varepsilon, \sigma|\sigma_i, \sigma_{-i}^*) \tag{3}$$

where σ_i^* denotes the optimal strategy. That is, no alternative strategy (σ_i) yields a higher expected discounted profit than σ_i^* while its rival uses the strategy σ_{-i}^*.

Representation of Markov Perfect Equilibrium in Probability Space For computing the equilibrium, it is convenient to represent the equilibrium in probability space for this model. Each strategy profile σ is associated with a set of conditional choice probabilities (CCPs) for each firm; for firm i's, this CCP can be written as

$$P_i^{\sigma}(a_i = a|\boldsymbol{s}) = \int I\{\sigma_i(\boldsymbol{s}, \varepsilon_i) = a\} g_i(\varepsilon_i) d\varepsilon_i. \tag{4}$$

where $a \in \mathcal{A}$, and $g_i(\cdot)$ is the probability density function of ε_i.

Following Aguirregabiria and Mira (2007), we define an integrated value function $V_i(\boldsymbol{s}, \sigma) \equiv \int \tilde{V}_i(\boldsymbol{s}, \varepsilon_i, \sigma) g_i(\varepsilon_i) d\varepsilon_i$. The integrated value function can expressed as a function of the CCPs:

$$\begin{aligned} V_i\left(s; \mathbf{P}^{\sigma}\right) =& \pi_i(s) + \sum_{a_i \in \mathcal{A}} P_i^{\sigma}\left(a_i|s\right) \left[C_i(a_i, n_i, z) + e_i(a_i, s; \mathbf{P}^{\sigma})\right] \\ &+ \beta \mathbb{E}\left[V_i\left(s'; \mathbf{P}^{\sigma}\right)|s; \mathbf{P}^{\sigma}\right] \end{aligned} \tag{5}$$

where $\mathbf{P}^{\sigma}$ is a vector that summarizes the CCPs of all firms associated with strategy σ; $e_i(a_i, \boldsymbol{s}; \mathbf{P}^{\sigma})$ is the conditional expectation of ε_i given that action a_i is taken at state $\boldsymbol{s}$.[1] In particular, the vector $\mathbf{V}_i\left(\mathbf{P}^{\sigma}\right)$, which stacks the integrated valuation function by state, and the CCPs are the fixed points of the following equation:

$$\mathbf{V}_i\left(\mathbf{P}^{\sigma}\right) = \left(I - \beta F\right)^{-1}\left[\boldsymbol{\pi}_i + \mathbf{eve}_i\right] \tag{6}$$

where

$$\mathbf{eve}_i \equiv \sum_{a_i \in \mathcal{A}} \mathbf{P}_i^{\sigma}\left(a_i\right) * \left[\boldsymbol{C}_i\left(a_i\right) + \mathbf{e}_i\left(a_i; \mathbf{P}^{\sigma}\right)\right], \tag{7}$$

I is the identity matrix; F is the transition matrix of states, which is a function of both $\mathbf{P}^{\sigma}$ and the Markov transition probabilities of z. $\boldsymbol{\pi}_i$ is a vector that stacks the state-specific element $\pi_i(s)$. $\mathbf{P}_i^{\sigma}\left(a_i\right)$ is a vector that stacks $P_i^{\sigma}\left(a_i|s\right)$ by state; $\mathbf{C}_i\left(a_i\right)$ and $\mathbf{e}_i\left(a_i; \mathbf{P}^{\sigma}\right)$ are vectors that stack $C_i\left(a_i, n_i, z\right)$ and $e_i(a_i, s; \mathbf{P}^{\sigma})$ by state respectively. The notation "$*$" is an element-by-element multiplication operator.

The representation of the MPE using CCPs is the main functional form that we deploy in the decomposition to follow. To this end, we define two additional terms which will be used repeatedly

[1] Hotz and Miller (1993) show that this conditional expectation $e_i(a_i, \boldsymbol{n}, z, \mathbf{P}^{\sigma})$ is a function of $P_i^{\sigma}\left(a_i|s\right)$ and the density function $g_i(\cdot)$ only. When ε follows an extreme value type I distribution, $e_i(a_i, s, \mathbf{P}^{\sigma}) = \sigma_{\varepsilon}\left(\gamma - \ln P_i^{\sigma}(a_i|s)\right)$, where σ_{ε} is the scale parameter of ε, and γ is the Euler constant.

in the decomposition:

$$\boldsymbol{\Upsilon}_{\pi_i} \equiv (I - \beta F)^{-1} \boldsymbol{\pi}_i \tag{8}$$

$$\boldsymbol{\Upsilon}_{eve_i} \equiv (I - \beta F)^{-1} \mathbf{eve}_i \tag{9}$$

As can be seen, $\mathbf{V}_i(\mathbf{P}^{\sigma}) = \boldsymbol{\Upsilon}_{\pi_i} + \boldsymbol{\Upsilon}_{eve_i}$, where $\boldsymbol{\Upsilon}_{\pi_i}$ is the net present value (NPV) of all firm i's profits from product competition, and $\boldsymbol{\Upsilon}_{eve_i}$ summarizes the NPV of all payoffs related to entry and exit costs. In the decomposition, we concentrate on the $\boldsymbol{\Upsilon}_{\pi_i}$ component of firm i's integrated value function because it contains firm i's entry deterrence motives.

Generalizing the retail-expansion model to a quality ladder model with investment As mentioned previously, even though our setting reflects competition between retail chains, the model can be easily interpreted as a quality ladder model where investment decisions are the key consideration. In particular, in the retail setting, firms' increasing and contracting the number of stores can be seen as investing and divesting. Adding a store involves investment in a new building or renovation of an existing building; closing a store involves selling off existing assets, which is divestment. Having a higher number of stores in a market improves the retail chain's product quality because consumers do not need to travel far to access a store or wait for long before being served. In this regard, a chain's expansion and contraction is equivalent to a firm's moving up and down the quality ladder in a quality-investment setting. Although most quality ladder models do not have the action of divestment, they do incorporate depreciation; that is, with some probability, a firm will slide down the quality ladder without investment. Given these similarities, the retail model in this paper can be treated as a quality ladder model.

The main difference between a retail-expansion and quality-investment interpretation of our model lies in how entry and exit are treated. In a retail-expansion setting, any increase in n_i is treated as an entry, and any decrease, an exit, whereas in an investment setting, only the change in n_i from 0 to 1 is treated as an entry, and the shift of n_i from 1 to 0 is an exit. These differences in the treatment of entry and exit affects the definitions of entry deterrence (and thus, their measurement) in these two settings. In the decomposition below, we isolate out the entry-deterrence motives of firms separately under each setting.

3 Measuring Entry Deterrence Motives

To quantify the deterrence motives, we use a decomposition of the equilibrium conditions. Through the decomposition, we identify the underlying motives behind a firm's actions at each state. We then break down these motives into a few main components: the marginal benefit of entry related to entry costs and scrap values, the marginal benefit in profit from product competition if current entry does not affect rivals' future actions, and most importantly, the marginal benefit from deterring the rivals in the next period. This last component is a firm's entry deterrence motive, and the resulting metric in percentages characterizes the degree of aggression in a firm's equilibrium strategy (i.e., the proportion to which deterrence motives account for all entry motives).

We begin by presenting some relevant empirical and theoretical contexts for our framework in Subsection 3.1. The decomposition and definitions of entry deterrence in each setting are described in Subsection 3.2. We construct the metric that measures firms' aggressiveness in an MPE in Subsection 3.3, while in Subsection 3.4, we illustrate theoretically the set of conduct restrictions that shut down firms' deterrence motives. Finally, we discuss how our approach compares to the measures of preemption in the existing literature in Subsection 3.5.

3.1 Relevant Contexts

Conceptually, entry deterrence has been described in the past literature as investments (with sunk costs) made by incumbent firms designed to block, slow-down, or push-out competitors (e.g., Dixit, 1980; Wilson, 1992). Examples of such actions that can impact anticipated rival entry decisions include idle capacity (e.g., Conlin and Kadiyali, 2006; Cookson, 2018; Gil et al., 2021; Dafny, 2005), IT infrastructure (e.g., Seamans, 2012), product proliferation (e.g., Bonanno, 1987; Shankar, 1999, 2006), product announcements (e.g., Haan, 2003), advertising expenditure (e.g., Ellison and Ellison, 2011; Shankar, 1997), pricing (e.g., Besanko et al., 2019; Chang and Sokol, 2022; Donnenfeld and Weber, 1995; Kadiyali, 1996; Sriram and Kadiyali, 2009; Sweeting, Roberts, and Gedge, 2020), omnichannel entry (e.g., Liu, Gupta, and Zhang, 2006), organizational form (e.g., Nishida and Yang, 2020), and acquisition of competitors (e.g., Cunningham, Ederer, and Ma, 2021). Similar to this past work, we also closely follow this concept of entry deterrence.

3.2 Decomposition and Definition

We do the decomposition and define deterrence motives first in the retail setting. Then we demonstrate how they apply in the quality-investment setting. Note that in practice, the decomposition (and thus measure of deterrence motives) should only be constructed for cases in which $\frac{\partial \pi_i(\cdot)}{\partial n_{-i}} < 0$; that is, firm i's profit decreases in the number of rivals' stores (i.e., firms i and $-i$ are mutual competitors). We point this out as some empirical settings might have cases in which $\frac{\partial \pi_i(\cdot)}{\partial n_{-i}} > 0$, due to potential positive spillovers between brands (e.g., Shen and Xiao, 2014; Vitorino, 2012; Yang, 2020); in these cases, a firm's strategic consideration is not labeled as entry deterrence[2]

The first step in this decomposition is to write out the Markov perfect equilibrium conditions for the firms. At any state, firm i's equilibrium CCPs must satisfy the following conditions:

$$\boldsymbol{P}_i(s) = G\left(\Delta\tilde{V}_i(s,1,0), \Delta\tilde{V}_i(s,0,-1)\right) \tag{10}$$

where $\boldsymbol{P}_i(s) = (P_i(1|s), P_i(0|s), P_i(-1|s))$ is a vector of firm i's equilibrium CCPs at state (s) with $\sum_{a=-1}^{1} P_i(a|s) = 1$. $G(\cdot)$ is cumulative density function (CDF) of ε; it maps the choice specific value differences onto the probability space. Hotz and Miller (1993) show that under a set of regularity conditions, $G(\cdot)$ is invertible. $\Delta\tilde{V}_i(s,1,0)$ and $\Delta\tilde{V}_i(s,0,-1)$ represent differences between firm i choice-specific value functions: $\Delta\tilde{V}_i(s,1,0) \equiv \tilde{V}_i(s,\varepsilon_i(1),a_i=1|\mathbf{P}) - \tilde{V}_i(s,\varepsilon_i(0),a_i=0|\mathbf{P})$ and $\Delta\tilde{V}_i(s,0,-1) \equiv \tilde{V}_i(s,\varepsilon_i(0),a_i=0|\mathbf{P}) - \tilde{V}_i(s,\varepsilon_i(-1),a_i=-1|\mathbf{P})$.

Inverting $G(\cdot)$ and expanding terms in $\Delta\tilde{V}_i(\cdot)$ gives us the following equilibrium conditions that link firms' CCPs to their marginal benefits of entry:

$$G_1^{-1}(\boldsymbol{P}_i(s)) = -\kappa_i^+(s_i) + \beta\sum_{a_{-i}}\sum_{z'} P_{-i}(a_{-i}|s) f(z'|z)\left[V_i(n_i+1, n_{-i}+a_{-i}, z') - V_i(n_i, n_{-i}+a_{-i}, z')\right], \forall 0 \le n_i < M. \tag{11}$$

$$G_2^{-1}(\boldsymbol{P}_i(s)) = -\kappa_i^-(s_i) + \beta\sum_{a_{-i}}\sum_{z'} P_{-i}(a_{-i}|s) f(z'|z)\left[V_i(n_i, n_{-i}+a_{-i}, z') - V_i(n_i-1, n_{-i}+a_{-i}, z')\right], \forall 0 < n_i \le M. \tag{12}$$

where $G_1^{-1}(\cdot)$ and $G_2^{-1}(\cdot)$ simply denote the first and second elements of $G^{-1}(\cdot)$, and $f(\cdot)$ is the Markov transition probability function of z. Note that if ε follows an extreme value type 1 distribution, then $G_1^{-1}(\cdot) = \ln(P_i(+1|s)/P_i(0|s))$, and $G_2^{-1}(\cdot) = \ln(P_i(0|s)/P_i(-1|s))$.

Together, equations 11 and 12 serve as both sufficient and necessary conditions for the equilibrium CCPs. The left hand sides (LHSs) of these equations are functions of only CCPs, and the right hand sides (RHSs) represent the marginal benefits of having one additional store. The RHS of equation 11 is the marginal benefit of opening a store, while the RHS of equation 12 is the benefit of not closing a store. Changes in the marginal benefits in these equations directly affect firms' probabilities of entry or not closing a store. In particular, the larger the RHSs of these two

[2] We refer the reader to the empirical application (Section 4) for an example of how to deal with such cases.

equations, the higher the probabilities of opening a store store or not closing one. Decomposing these marginal benefits is the key to formulating the deterrence motives.

As an illustration, we focus on decomposing the RHS of equation 11 to identify entry deterrence motives. The decomposition of equation 12 is analogous. As can be seen, in equation 11 the trade-off faced by a firm between opening a store and doing nothing is that firm i incurs an average entry cost of $\kappa_i^+(s_i)$ now, but receives $\sum_{a_{-i}}\sum_{z'} P_{-i}(a_{-i}|s) f(z'|z)\left[V_i(n_i+1, n_{-i}+a_{-i}, z') - V_i(n_i, n_{-i}+a_{-i}, z')\right]$ in the next period. Expanding $V_i(n_i+1, n_{-i}+a_{-i}, z') - V_i(n_i, n_{-i}+a_{-i}, z')$ into the $\Upsilon_{\pi_i}(\cdot)$ and $\Upsilon_{eve_i}(\cdot)$ terms, we can separate out the various components of firm i marginal benefit of entry:

$$V_i(n_i+1, n_{-i}+a_{-i}, z') - V_i(n_i, n_{-i}+a_{-i}, z') = A_{1i}(s) + B_{1i}(s) + C_{1i}(s), \text{ where} \tag{13}$$

$$A_{1i}(s) = \Upsilon_{eve_i}(s'_{+1}) - \Upsilon_{eve_i}(s'_0) \tag{14}$$

$$B_{1i}(s) + C_{1i}(s) = \Upsilon_{\pi_i}(s'_{+1}) - \Upsilon_{\pi_i}(s'_0), \text{and} \tag{15}$$

$$\begin{aligned} B_{1i}(s) = {} & \pi_i(s'_{+1}) - \pi_i(s'_0) \\ & + \beta \sum_{z''} f(z''|z') \left(\sum_{k=-2}^{1} \sum_{a'_{-i}} P_{-i}(a'_{-i}|s'_0) \left(P_i(k|s'_{+1}) - P_i(k+1|s'_0)\right) \Upsilon_{\pi_i}(n_i+1+k, n_{-i}+a_{-i}+a'_{-i}, z'') \right) \end{aligned} \tag{16}$$

$$C_{1i}(s) = \beta \sum_{z''} f(z''|z') \left(\sum_{k=-1}^{1} \sum_{a'_{-i}} P_i(k|s'_{+1}) \left(P_{-i}(a'_{-i}|s'_{+1}) - P_{-i}(a'_{-i}|s'_0)\right) \Upsilon_{\pi_i}(n_i+1+k, n_{-i}+a_{-i}+a'_{-i}, z'') \right) \tag{17}$$

where z'' is the state of z two periods from now. $s'_{+1} = (n_i+1, n_{-i}+a_{-i}, z')$ and $s'_0 = (n_i, n_{-i}+a_{-i}, z')$. $\Upsilon_{\pi_i}(n_i+1+k, n_{-i}+a_{-i}+a'_{-i}, z'')$ is the NPV of all firm i's future profits from product competition at the state $(n_i+1+k, n_{-i}+a_{-i}+a'_{-i}, z'')$. The probabilities of actions that are not in firms' choice set, such as $P_i(-2|s'_{+1})$ and $P_i(2|s'_0)$, are equal to 0.

Equation 13 formulates the essential decomposition of firm i's entry motives. Component $A_{1i}(s)$, along with $-\kappa_i^+(s_i)$, represents the marginal benefit of entry that is related to entry costs and scrap values. If the firm enters, it pays the average entry cost $\kappa_i^+(s_i)$ in the current period, but receives a future payoff of $A_{1i}(s)$ through savings in entry costs and growth in scrap values from all future periods. For example, if firm i knows that the entry costs will increase substantially in the future, it might decide to open an outlet today in order to save costs; similarly, if the firm foresees that scrap values will be worth much more in the future than the current entry cost, it may decide to open a store today in order to make a profit off selling the store in the future. Both savings in entry costs and growth in scrap values make a firm enter the market early and expand its store network, but they have nothing to do with the purpose of deterring rivals.

Component $B_{1i}(s)$ summarizes the marginal benefit of entry in future profits from product competition when its current entry does not affect rivals' actions in the next period (i.e., the "direct" effect alluded to in the introduction). $\pi_i(s'_{+1}) - \pi_i(s'_0)$ represents the next-period's profit differential if firm i enters today. This differential is the immediate product of competition in the current period, where firms take each other's CCPs as given and choose an optimal action; their entry and exit decisions do not have an impact on product competition until the following period. The remainder of component $B_{1i}(s)$ is the marginal benefit in future profits from the second period onward. It captures how firm i's entry today affects profits by influencing only its own action not the rivals' actions in the next period; as can be seen, the rivals' actions are fixed at $P_{-i}(a'_{-i}|s'_0)$ in the next period; the marginal benefit is generated by the difference between firm i's CCPs in the next period, i.e. $P_i(k|s'_{+1}) - P_i(k+1|s'_0)$.

Component $C_{1i}(s)$ captures the marginal benefit from deterring the rivals in the next period (i.e., the "indirect" effect alluded to in the introduction). As can be seen, in this component, firm i's CCP in the next period is fixed at $P_i(k|s'_{+1})$, and the marginal benefit is generated by the difference between the rivals' next-period CCPs if firm i opens a new outlet today and those CCPs if firm i does not, i.e. $P_{-i}(a'_{-i}|s'_{+1}) - P_{-i}(a'_{-i}|s'_0)$. It can be shown that component $C_{1i}(s)$ is always positive under a set of conditions that are commonly observed in the real world. Proposition 1 in Appendix A states this formally. A positive $C_{1i}(s)$ indicates that by affecting how rivals behave in the next period, firm i's entry in the current period increases its profits from future periods. This gain in future profits is firm i's deterrence motive. Definition 1 below states the motive formally and adds $\beta \sum\limits_{a_{-i}} \sum\limits_{z'} P_{-i}(a_{-i}|s) f(z'|z)$ in front of $C_{1i}(s)$ to account for state transitions. In addition, Definition 1 incorporates the counterpart of $C_{1i}(s)$, denoted as $C_{2i}(s)$, in the decomposition of equation 12. Let $s'_{-1} = (n_i - 1, n_{-i} + a_{-i}, z')$ and $C_{2i}(s) = \beta \sum_{z''} f(z''|z') \left(\sum\limits_{k=-2}^{1} \sum\limits_{a'_{-i}} P_i(k|s'_0) \left(P_{-i}(a'_{-i}|s'_0) - P_{-i}(a'_{-i}|s'_{-1}) \right) \Upsilon_{\pi_i}(n_i + k, n_{-i} + a_{-i} + a'_{-i}, z'') \right)$. Then Definition 1 states the deterrence motives for firm i by affecting rivals' actions in the next period.

DEFINITION 1

$\beta \sum\limits_{a_{-i}} \sum\limits_{z'} P_{-i}(a_{-i}|s) f(z'|z) C_{1i}(s)$ and $\beta \sum\limits_{a_{-i}} \sum\limits_{z'} P_{-i}(a_{-i}|s) f(z'|z) C_{2i}(s)$ are firm i's deterrence motives at state (n_i, n_{-i}, z) from affecting rivals' behaviors in the next period.

We want to emphasize that Definition 1 does not account for the firm's deterrence motives from affecting rivals' actions in *all* future periods. The reason is that component $B_{1i}(s)$ still contains gains from deterrence. To see this clearly, we can further decompose $B_{1i}(s)$ as

$$B_{1i}(s) = \pi_i(s'_{+1}) - \pi_i(s'_0) + \beta \sum_{z''} f(z''|z') \left(\sum_{a'_{-i}} P_{-i}(a'_{-i}|s'_0)(H_i(s) + I_i(s)) \right), \text{ where} \tag{18}$$

$$H_i(s) = \sum_{a'_i} \left(P_i(a'_i|s'_{+1}) - P_i(a'_i|s'_0) \right) \Upsilon_{\pi_i}(n_i + a'_i, n_{-i} + a_{-i} + a'_{-i}, z'')$$

$$I_i(s) = \sum_{a'_i} P_i(a'_i|s'_{+1})(\Upsilon_{\pi_i}(n_i + 1 + a'_i, n_{-i} + a_{-i} + a'_{-i}, z'') - \Upsilon_{\pi_i}(n_i + a'_i, n_{-i} + a_{-i} + a'_{-i}, z''))$$

As can be seen, the $I_i(s)$ component includes the difference between $\Upsilon_{\pi_i}(n_i + 1 + a'_i, n_{-i} + a_{-i} + a'_{-i}, z'')$ and $\Upsilon_{\pi_i}(n_i + a'_i, n_{-i} + a_{-i} + a'_{-i}, z'')$; that is, the difference between firm i NPV of profits at a state with one more store and the NPV without the additional store. As shown in the previous decomposition, namely equation 15, this type of difference contains deterrence motives like $C_{1i}(s)$. To take out the deterrence motives for all future periods at all future states, we must construct an alternative value, denoted by $\widehat{\Upsilon}_{\pi_i}(\cdot)$, where the rivals' CCPs are held constant across all firm i's states for *all* periods. Definition 1 provides guidance on how to construct this term; it implies that to eliminate deterrence motives at all states, the following condition must hold:

$$P_{-i}(a'_{-i}|n_i + 1, n'_{-i}, z'') = P_{-i}(a'_{-i}|n_i, n'_{-i}, z''), \forall a'_{-i} \in \mathcal{A}^{N-1}, n_i < M, n'_{-i}, z'', \text{which is equivalent to}$$

$$P_{-i}(a'_{-i}|n_i, n'_{-i}, z'') = P_{-i}(a'_{-i}|0, n'_{-i}, z''), \forall a'_{-i} \in \mathcal{A}^{N-1}, n_i, n'_{-i}, z''. \tag{19}$$

Equation 19 says if the rivals' CCPs at *any* of firm i's states are replaced with those at the states when firm i is not in the market, firm i's deterrence motives will be eliminated at every state. $\widehat{\Upsilon}_{\pi_i}(\cdot)$ can then be formulated as an element of the state-stacked vector $\widehat{\boldsymbol{\Upsilon}}_{\pi_i}$:

$$\widehat{\boldsymbol{\Upsilon}}_{\pi_i} \equiv (I - \beta\widehat{F})^{-1}\boldsymbol{\pi}_i, \tag{20}$$

where $\widehat{F}$ is formed by replacing all $P_{-i}(a_{-i}|n_i, n_{-i}, z)$ with $P_{-i}(a_{-i}|0, n_{-i}, z)$, $\forall a_{-i} \in \mathcal{A}^{N-1}, n_i, n_{-i}, z$ in the transition matrix F.

With $\widehat{\Upsilon}_{\pi_i}(\cdot)$ in hand, we can decompose $V_i(n_i + 1, n_{-i} + a_{-i}, z') - V_i(n_i, n_{-i} + a_{-i}, z')$ to extract firm i's deterrence motives in all future periods:

$$V_i(n_i + 1, n_{-i} + a_{-i}, z') - V_i(n_i, n_{-i} + a_{-i}, z') = A_{1i}(s) + BA_{1i}(s) + CA_{1i}(s), \text{ where} \tag{21}$$

$$A_{1i}(s) = \Upsilon_{eve_i}(s'_{+1}) - \Upsilon_{eve_i}(s'_0) \tag{22}$$

$$BA_{1i}(s) = \widehat{\Upsilon}_{\pi_i}(s'_{+1}) - \widehat{\Upsilon}_{\pi_i}(s'_0) \tag{23}$$

$$CA_{1i}(s) = (\Upsilon_{\pi_i}(s'_{+1}) - \Upsilon_{\pi_i}(s'_0)) - \left(\widehat{\Upsilon}_{\pi_i}(s'_{+1}) - \widehat{\Upsilon}_{\pi_i}(s'_0) \right) \tag{24}$$

In this decomposition, $BA_{1i}(s)$ represents the change in firm i's NPV of profits from product competition if firm i's entry today has no impact on rivals' actions in *all* future periods and at *all* states. $CA_{1i}(s)$ is the remainder, which represents the gain in firm i's NPV of profits by affecting rivals' behaviors in *all* future states if it chooses entry today. Definition 2 formally states this claim and incorporates the counterpart of $CA_{1i}(s)$, denoted by $CA_{2i}(s)$, from equation 12. Let $CA_{2i}(s) = \left(\Upsilon_{\pi_i}(s'_0) - \Upsilon_{\pi_i}(s'_{-1})\right) - \left(\widehat{\Upsilon}_{\pi_i}(s'_0) - \widehat{\Upsilon}_{\pi_i}(s'_{-1})\right)$.

DEFINITION 2

$\beta \sum_{a_{-i}} \sum_{z'} P_{-i}(a_{-i}|s) f(z'|z) CA_{1i}(s)$ and $\beta \sum_{a_{-i}} \sum_{z'} P_{-i}(a_{-i}|s) f(z'|z) CA_{2i}(s)$ are firm i's deterrence motives at state (n_i, n_{-i}, z) from affecting rivals' behaviors in *all* future periods.

3.2.1 Decomposition for Investment Setting

Definition 1 applies to the retail expansion setting, where all strategic considerations are linked to the deterrence of competitor entry. However, for settings where investment is the key strategic decision, firms' strategies involve *both* entry and investment. Consequently, Definition 1 includes both the motive of deterring rivals' entry and that of discouraging rivals' investment. To identify the deterrence motive in this setting, we need to disentangle these motives and apply an additional layer of decomposition to the terms in Definition 1.

The key step for establishing this decomposition is to focus on those future states at which the rivals have the option to enter or exit the market; that is, for a rival firm, say firm j, its next period's state is either $n'_j = 0$ or $n'_j = 1$. In these two cases, firm i has the opportunity to choose actions strategically today in order to deter firm j's entry or induce its exit in the next period. The decomposition of firms' equilibrium conditions in these two cases give us the definition of firm i's motives to deter the entry of firm j and to induce the exit of firm j respectively. We leave both the detailed derivations and the formal statement of the definitions to Appendix B.

3.3 Measure

To establish how important firms' deterrence motives are in relation to confounding alternatives, such as economies of density, favorable entry costs, or scrap value growth, we develop a measure of deterrence motives. Again, we focus on the retail setting first and then extend the measure to the investment setting. In the retail setting, the measure of how aggressive a firm behaves in an equilibrium is formulated as follows:

$$DM_i = \sum_{s \in \mathcal{S}} h(s) PI_i(s), \tag{25}$$

where $\mathcal{S}$ denotes the set of all states; $h(s)$ is the probability of s in the steady-state distribution of states[3] and $PI_i(s)$ is the state-specific measure of deterrence motives for firm i and has the following form:

$$PI_i(s) = \frac{\mathbb{1}\{\sum_{k=1}^{2}\widetilde{CA}_{ki}(s)>0\}\sum_{k=1}^{2}\widetilde{CA}_{ki}(s)}{\mathbb{1}\{\sum_{k=1}^{2}\widetilde{A}_{ki}(s)>0\}\sum_{k=1}^{2}\widetilde{A}_{ki}(s)+\mathbb{1}\{\sum_{k=1}^{2}\widetilde{BA}_{ki}(s)>0\}\sum_{k=1}^{2}\widetilde{BA}_{ki}(s)+\mathbb{1}\{\sum_{k=1}^{2}\widetilde{CA}_{ki}(s)>0\}\sum_{k=1}^{2}\widetilde{CA}_{ki}(s)+\mathbb{1}\{\widetilde{\kappa}_i^+(s_i)>0\}\widetilde{\kappa}_i^+(s_i)+\mathbb{1}\{\widetilde{\kappa}_i^-(s_i)>0\}\widetilde{\kappa}_i^-(s_i)}, \tag{26}$$

$$\widetilde{A}_{1i}(s) = \beta \sum_{a_{-i}} \sum_{z'} P_{-i}(a_{-i}|s) f(z'|z) \left(\Upsilon_{eve_i}(s'_{+1}) - \Upsilon_{eve_i}(s'_0)\right)$$

$$\widetilde{BA}_{1i}(s) = \beta \sum_{a_{-i}} \sum_{z'} P_{-i}(a_{-i}|s) f(z'|z) \left(\widehat{\Upsilon}_{\pi_i}(s'_{+1}) - \widehat{\Upsilon}_{\pi_i}(s'_0)\right)$$

$$\widetilde{CA}_{1i}(s) = \beta \sum_{a_{-i}} \sum_{z'} P_{-i}(a_{-i}|s) f(z'|z) \left(\left(\Upsilon_{\pi_i}(s'_{+1}) - \Upsilon_{\pi_i}(s'_0)\right) - \left(\widehat{\Upsilon}_{\pi_i}(s'_{+1}) - \widehat{\Upsilon}_{\pi_i}(s'_0)\right)\right)$$

$$\widetilde{A}_{2i}(s) = \beta \sum_{a_{-i}} \sum_{z'} P_{-i}(a_{-i}|s) f(z'|z) \left(\Upsilon_{eve_i}(s'_0) - \Upsilon_{eve_i}(s'_{-1})\right)$$

$$\widetilde{BA}_{2i}(s) = \beta \sum_{a_{-i}} \sum_{z'} P_{-i}(a_{-i}|s) f(z'|z) \left(\widehat{\Upsilon}_{\pi_i}(s'_0) - \widehat{\Upsilon}_{\pi_i}(s'_{-1})\right)$$

$$\widetilde{CA}_{2i}(s) = \beta \sum_{a_{-i}} \sum_{z'} P_{-i}(a_{-i}|s) f(z'|z) \left(\left(\Upsilon_{\pi_i}(s'_0) - \Upsilon_{\pi_i}(s'_{-1})\right) - \left(\widehat{\Upsilon}_{\pi_i}(s'_0) - \widehat{\Upsilon}_{\pi_i}(s'_{-1})\right)\right)$$

$$\widetilde{\kappa}_i^+(s_i) = -\kappa_i^+(s_i) + e_i(1, s)$$

$$\widetilde{\kappa}_i^-(s_i) = -\kappa_i^-(s_i) - e_i(-1, s)$$

In equation 26, $\widetilde{A}_{1i}(s)$, $\widetilde{A}_{2i}(s)$, $\widetilde{BA}_{1i}(s)$ and $\widetilde{BA}_{2i}(s)$ are simply the $A_{1i}(s)$, $A_{2i}(s)$, $BA_{1i}(s)$ and $BA_{2i}(s)$ terms with the state transition accounted for.[4] Along with $\widetilde{\kappa}_i^+(s_i)$, and $\widetilde{\kappa}_i^-(s_i)$, these tilda terms represent entry (or stay) motives other than deterrence. They are multiplied by a sign indicator to ensure that they are accounted for as entry motives only when they are positive. The entry cost, $-\widetilde{\kappa}_i^+(s_i)$, accounts for both the average entry cost, $\kappa_i^+(s_i)$, and the average of idiosyncratic shocks to the entry costs conditional on entry being optimal, $e_i(1, s)$. Given that $e_i(1, s)$ is a function of firm i's equilibrium CCPs, $-\widetilde{\kappa}_i^+(s_i)$ represents the actual average entry

[3] Note that n empirical applications, the steady-state distribution can be replaced with the empirical distribution of states.

[4] $A_{2i}(s) = \Upsilon_{eve_i}(s'_0) - \Upsilon_{eve_i}(s'_{-1})$ and $BA_{2i}(s) = \widehat{\Upsilon}_{\pi_i}(s'_0) - \widehat{\Upsilon}_{\pi_i}(s'_{-1})$ are the counterparts of $A_{1i}(s)$ and $BA_1(s)$ from equation 12.

costs firm i pays in equilibrium at state s. Similarly, the scrap value $-\widetilde{\kappa}_i^-(s_i)$ captures the actual average scrap values firm i receives in equilibrium.

To see how these cost and benefit components fit into firm i's equilibrium conditions, we can rewrite equations 11 and 12 as follows:

$$-\kappa_i^+(s_i) + \widetilde{A}_{1i}(s) + \widetilde{BA}_{1i}(s) + \widetilde{CA}_{1i}(s) + e_i(1,s) - e_i(0,s) = 0 \tag{27}$$

$$-\kappa_i^-(s_i) + \widetilde{A}_{2i}(s) + \widetilde{BA}_{2i}(s) + \widetilde{CA}_{2i}(s) + e_i(0,s) - e_i(-1,s) = 0 \tag{28}$$

These equations are based on the fact that in equilibrium, the conditional expectations of firm i's choice-specific value functions are equal to each other for any distribution of ε; that is, $E(\tilde{V}_i\left(s,\varepsilon_i(1),a_i=1\right)|a_i^*=1) = E(\tilde{V}_i\left(s,\varepsilon_i(0),a_i=0\right)|a_i^*=0) = E(\tilde{V}_i\left(s,\varepsilon_i(-1),a_i=-1\right)|a_i^*=-1)$. The proof of this property is provided in Appendix C.

Equations 27 and 28 represent firm i's indifference conditions between choice alternatives. Equation 27 is the firm's indifference between adding one outlet and leaving the number of outlets unchanged, while equation 28 is the indifference between leaving the number of outlets unchanged and closing an outlet. Adding up the two equations, we get the indifference between opening a store and closing a store:

$$-(\kappa_i^+(s_i) - e_i(1,s)) - (\kappa_i^-(s_i) + e_i(-1,s)) + \sum_{k=1}^{2} \widetilde{A}_{ki}(s) + \sum_{k=1}^{2} \widetilde{BA}_{ki}(s) + \sum_{k=1}^{2} \widetilde{CA}_{ki}(s) = 0 \tag{29}$$

Equation 29 summarizes the marginal costs and benefits faced by firm i in both equations 27 and 28. In this equation, the marginal benefits of adding a store must equal the marginal costs. We collect the positive components, i.e. the marginal benefits, from this equation to construct the state-specific measure in equation 26. This measure thus represents the portion that deterrence motives account for out of all entry motives of firm i at state s.

Measure in the Investment Setting The measure in the quality-investment setting can be similarly constructed. The only differences are that the $\widetilde{BA}_{1i}(s)$, $\widetilde{BA}_{2i}(s)$, $\widetilde{CA}_{1i}(s)$ and $\widetilde{CA}_{2i}(s)$ components in equation 26 should be replaced by their counterparts in the investment setting, namely $\widetilde{BAI}_{1i}(s)$, $\widetilde{BAI}_{2i}(s)$, $\widetilde{CAI}_{1i}(s)$ and $\widetilde{CAI}_{2i}(s)$, whose functional forms can be found in Appendix B.

3.4 Conduct Restrictions

This section describes the analytical framework for conduct restrictions in retail settings and how our decomposition approach can fit into such analysis, as our definitions of deterrence motives yield natural conditions for minimizing or eliminating deterrence motives. This theoretical exposition of conduct restrictions serves two main purposes. First, it presents the analytical framework for policy, as these conduct restrictions can help provide guidance about how firms *should* behave absent deterrence motives. Second, this discussion will help provide an analytical link between our decomposition measure and the existing counterfactual-based approaches for establishing deterrence motives. By presenting the theoretical background behind conduct restrictions, we hope that such discussions will make it easier to relate our approach to various alternative methods available for quantifying deterrence motives; to some extent, we hope that this section serves as the theoretical basis for how our framework can complement the existing literature. In practice, there are numerous options for how a researcher or practitioner can prescribe the "preferred" entry strategies in the market, so conduct restrictions would require some additional discretion with respect to implementation, especially if there are many equilibrium strategies. As a matter of semantics, we label this exercise as implementing conduct restrictions, instead of counterfactuals because the conduct restrictions are a set and likely not unique under these restrictions.

Eliminating Deterrence Motives for All Periods To understand how firms should behave absent deterrence motives, we need a way to "shut down" these motives from all periods. To do so, we can set the deterrence motive terms in Definition 2 to 0. Firms' behaviors are then governed by the following conduct restrictions:

$$G_1^{-1}\left(\boldsymbol{P}_i^c(s)\right) = -\kappa_i^+(s_i) + \beta \sum_{a_{-i}} \sum_{z'} P_{-i}^c(a_{-i}|s) f(z'|z) \left[A_{1i}(s) + BA_{1i}(s)\right], \forall i, 0 \leq n_i < M. \tag{30}$$

$$G_2^{-1}\left(\boldsymbol{P}_i^c(s)\right) = -\kappa_i^-(s_i) + \beta \sum_{a_{-i}} \sum_{z'} P_{-i}^c(a_{-i}|s) f(z'|z) \left[A_{2i}(s) + BA_{2i}(s)\right], \forall i, 0 < n_i \leq M. \tag{31}$$

where the c superscript denotes constrained behaviors of firms under the conduct restrictions. In these restrictions, $A_{1i}(s)$, $A_{2i}(s)$, $BA_{1i}(s)$ and $BA_{2i}(s)$ are terms calculated based on equilibrium CCPs. The set of equations 30 and 31 produce a set of restricted CCPs for all firms. Note, however, that the CCPs that satisfy these restrictions may not be unique. Just as games can have multiple equilibria, equations 30 and 31 can produce multiple sets of CCPs. It is up to the anti-trust authority to prescribe which set of CCPs they would like to see being played in the market. The authors of this paper do not take a stance.

These conduct restrictions reserve the direct competition between firms. As can be seen from equations 30 to 31, firm i takes rivals CCPs $P_{-i}^c(a_{-i}|s)$ as given and respond optimally. The conduction restrictions also preserve all other entry motives of the firms. Investment motives through entry costs and scrap values are reflected in $A_{1i}(s)$ and $A_{2i}(s)$, while long-term operation motives though selling products to consumers are reflected in $BA_{1i}(s)$ and $BA_{2i}(s)$ terms. These conduct restrictions also allow firms to adjust their behaviors according to their states. As can be seen, firms' CCPs under the conduct restrictions are state-dependent.

Implementation of Conduct Restrictions in Practice In practice, firms' strategies in entry and exit probabilities may be difficult to monitor for antitrust authorities. We propose an analytical solution for implementing the conduct restrictions. Note that there is a one-to-one relationship between CCPs and the cutoff values of $\varepsilon(1)-\varepsilon(0)$ and $\varepsilon(0)-\varepsilon(-1)$ (Doraszelski and Satterthwaite, 2010). The CCPs can simply be translated into these cutoff values for the antitrust authorities to monitor. As an example, equation 30 can be simply rewritten as

$$\varepsilon_i(0)-\varepsilon_i(1) \leq -\kappa_i^+(s_i) + \beta \sum_{a_{-i}} \sum_{z'} P_{-i}^c(a_{-i}|s) f(z'|z) \left[A_{1i}(s) + BA_{1i}(s)\right], \forall i, 0 \leq n_i < M. \tag{32}$$

The RHS of inequality 32 can be computed from firms' restricted CCPs and the structural primitives of the model; it is therefore known to the antitrust authorities. The cutoff point for $\varepsilon_i(0)-\varepsilon_i(1)$ is then known. If the antitrust authorities know the detailed cost structure at each firm in the industry, they can simply approve an entry when $\varepsilon_i(0)-\varepsilon_i(1)$ is less than the threshold and and rejects one when it is greater.

3.5 Conceptual Differences with Alternative Approaches

We provide a brief discussion about our framework for measuring deterrence motives under the context of the extant literature. In particular, we describe conceptually how our framework differs from alternative techniques that rely on counterfactual designs to establish existence of deterrence (e.g., Igami and Yang, 2016; Zheng, 2016).

First, the decomposition approach allows a researcher to avoid making discretionary judgment calls about how exactly a counterfactual is implemented. For example, Igami and Yang (2016) and Zheng (2016) are examining similar counterfactual scenarios, in which the authors attempt to reduce preemption by eliminating competition, though the exact way they operationalize the counterfactuals are inherently different. Igami and Yang (2016) remove competition from one player for all periods, while Zheng (2016) removes it for a single period. Both papers eliminate direct competition, which is often deemed desirable, for a player for all periods or for one period. Other authors such as Hünermund et al. (2014) use the open-loop equilibrium concept and restrict firms' strategies to be independent across their rivals' incumbency states. These different implementations (and the assumptions attached to them) lead to inherently different counterfactual outcomes. The decomposition approach we develop allows a researcher to avoid such discretionary choices, as the object of interest is derived directly from the equilibrium conditions and can be directly interpreted as a deterrence motive without the need of any assumptions beyond the usual ones in an Ericson and Pakes (1995) framework for dynamic games. Nevertheless, our conduct restrictions can be used as counterfactuals where firms ignore their deterrence motives. When used as counterfactuals, our conduct restrictions do retain direct competition between players and allow firms' strategies to be state dependent, unlike in an open-loop equilibrium where firms only maximize their initial state values.

Second, the decomposition provides a measure of deterrence motives, which shows the importance of deterrence motives relative to other entry motives of firms. We believe this is informative beyond what typical counterfactual analyses in the literature can do. Counterfactual analyses typically compare equilibria and counterfactuals to reveal the existence of deterrence motives and the impact of deterrence motives. However, this type of comparison does not inform us of how much firms' equilibrium actions are driven by deterrence motives relative to all other motives. From this perspective, our decomposition approach complements the typical counterfactual analyses, as our approach can provide insights about the magnitude of deterrence motives relative to everything else. In contrast, past work has largely investigated the change in market outcomes, such as outlet growth (e.g., Igami and Yang, 2016), with and without deterrence motives; but it's not entirely clear whether the inferred gaps in outlet growth across the scenarios should be considered as small or large, let alone the comparability of these gaps if deterrence motives vary across firms and markets.

Finally, the comparison between equilibria and counterfactuals is usually not straightforward because in games, both equilibria and counterfactuals can face multiplicity. Which counterfactual should be used to compare with equilibrium requires additional assumptions. Taken together, our framework provides a complementary approach to the existing literature. More generally, many types of counterfactuals in dynamic models are at best set-identified (e.g., Kalouptsidi et al., 2021), absent normalization assumptions about model primitives like entry costs and scrap values (e.g., Aguirregabiria and Suzuki, 2014). We would expect similar identification conditions for dynamic games. Ultimately, the decomposition approach allows us to avoid evaluating hypothetical changes in the structural parameters (e.g., entry costs, competition sensitivity), so we are in theory able to circumvent this issue.

4 Case Study: Coffee Chain Dynamics in Toronto, Canada

In this section, we provide a novel empirical case-study about coffee chain dynamics that demonstrates the use of our measure for quantifying deterrence motives. The empirical analysis aims to answer two questions. First, to what extent do deterrence motives drive the industry dynamic patterns in the the coffee chain industry? Second, do we observe heterogeneity in the intensity of these motives across firms and markets? Answering these questions will help policy makers and managers establish more targeted and more effective policies about entry deterrence (i.e., identifying the "who" and "when" behind deterrence).

To proceed, we first present Subsection 4.1 that describes the empirical context. Subsection 4.2 follows, where we present our estimation approach. Finally, Subsection 4.3 summarizes the structural estimates, while Subsection 4.4 demonstrates the implementation of our measure.

4.1 Data

We make use of entry and exit data from coffee chains in Toronto, Canada. The products offered across these chains primarily center around coffee drinks, though they all offer a range of breakfast and lunch items (e.g., bagels, donuts, pastries, salads, sandwiches, soup). Coffee stores in Canada generated about \$5 billion in revenue in recent years, with an annual growth rate of about 2.7% (e.g., IBISWorld, 2021).

The years that our data covers span from 1989 to 2005. We focus on locations for the four largest chains in Toronto, namely Coffee Time, Country Style, Starbucks and Tim Hortons. Coffee Time and Country Style are regional chains (with presence primarily in the province of Ontario), while Starbucks and Tim Hortons have a national footprint. This location data was obtained using archived phone directories from the City of Toronto Reference Library or directly from the chains themselves (Coffee Time and Tim Hortons). For each store, we can then identify its exact address, as well as when they entered (and exited, if applicable). Toronto is an ideal city to study given that it is the most metropolitan and densely populated city in Canada, which would make it easier to study the impact of own and rival stores in close proximity of one another.

For all of these chains, the location and outlet growth decisions are made by the members of the real estate teams within each of the chains, whereby employees in these teams often specialize in small geographic regions when conducting the *pro forma* analysis. This process for selection locations applies regardless of whether the store is company-owned or franchised. Our market definition is based on small geographies that we manually create. In particular, we follow a similar (albeit slightly modified) clustering approach as Rozenfield et al. (2011) to delineate the markets. A similar approach has also been used by Cosman's (2014) study about nightclub industry dynamics, where geographic regions (i.e., bubble markets) are identified within a city. In particular, we follow these steps when identify these markets:

1. Choose a coffee store that is not yet assigned to a market area, and then draw a circle of radius 100 meters around that store in the downtown area, and 500 meters around the store in the suburban areas; this way, we allow for smaller geographic markets in downtown where most people walk, and larger markets in the suburbs where most people drive.[5] The set of stores in this circle are then assigned to the same market as the store.

2. For each newly assigned store from the previous step, draw a new circle of radius 100 meters for downtown stores (500 meters for suburban stores) and assign all not-yet-assigned stores to the same market area.

3. Repeat the previous step until the newly-drawn circles no longer incorporate any new stores. The union of all circles from the first two steps will then define the market area.

4. Repeat the three steps starting with new unassigned stores to define new market areas until no unassigned stores remain.

5. Manual checks are conducted to ensure that coffee stores within a mall are not lumped together with those outside into one market, as well as coffee shops on the opposite sides of highways are not included into one geographic market. In addition, if a coffee shop is located away from a cluster of shops slightly farther than 500 meters (e.g. 600-800 meters), we lump that shop into the cluster as one market. However, if a shop is not within 1 km of any other shops, we treat it as its own market.

Through this process, we identify $M = 142$ isolated geographic markets. After defining the markets, we then match them to market size indicators obtained from the Government of Canada. The indicators include population and income, which come from the Canadian Census Profiles (1990, 1991, 1996, 2001, 2006) and are at the Census tract level. We then identify Census tracts that each bubble market falls into, and match each market to the Census information accordingly.

[5] A radius of 100 meters is reasonable for the distance that consumers are willing to walk downtown. Toronto's weather is very cold in the winter, which usually lasts from October to May. For the suburbs, although consumers can easily drive more than 500 meters, our map of the coffee shops shows that in most clusters of coffee shops, the shops are within 500 meters of each other. We therefore choose 500 meters as the radius.

In the cases for which a bubble market intersects more than one Census tract, we take the average values of the market size indicators. Furthermore, for the non-Census years, the missing population and income values are imputed based on their growth rates.

Figure 1 presents the store count distribution across the 142 bubble markets of all outlets that were ever active during the time period we study. A majority of the markets (nearly 85% of them) eventually have 2 or more outlets. Table 1 provides the distribution of store counts across all markets and years for each of the the four chains. A majority of the sample contains markets in which a chain has at most 2 outlets, though there is a small percentage of observations in which there are 3 or more outlets. When we look at the aggregate dynamics of store counts, it is apparent that the coffee chain industry in Canada has experienced changes in market leadership over time.

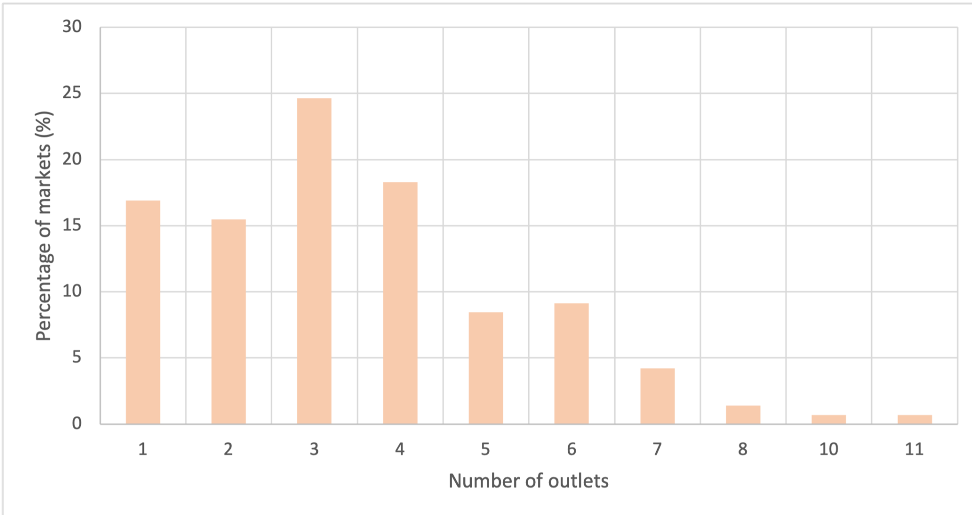
Figure 2 provides a visualization of outlet growth for each of the chains. In the early years, Coffee Time and Country Style were among the dominant players in the industry, while Starbucks and Tim Hortons both experienced rapid growth in outlets, with growth starting to accelerate after 1995. A noticeable pattern is that the rapid growth of these increasingly dominant chains coincide with slower or even decreasing growth for Coffee Time and Country Style. While it is difficult to ascertain the exact cause of these patterns with descriptive analysis alone, these patterns are plausibly consistent with the notion that Starbucks and/or Tim Hortons might have used market saturation via market growth to halt and even hinder the growth of its rivals. An important empirical question that arises from these descriptive patterns is whether or not Starbucks and/or Tim Hortons drove out Coffee Time and Country Style.

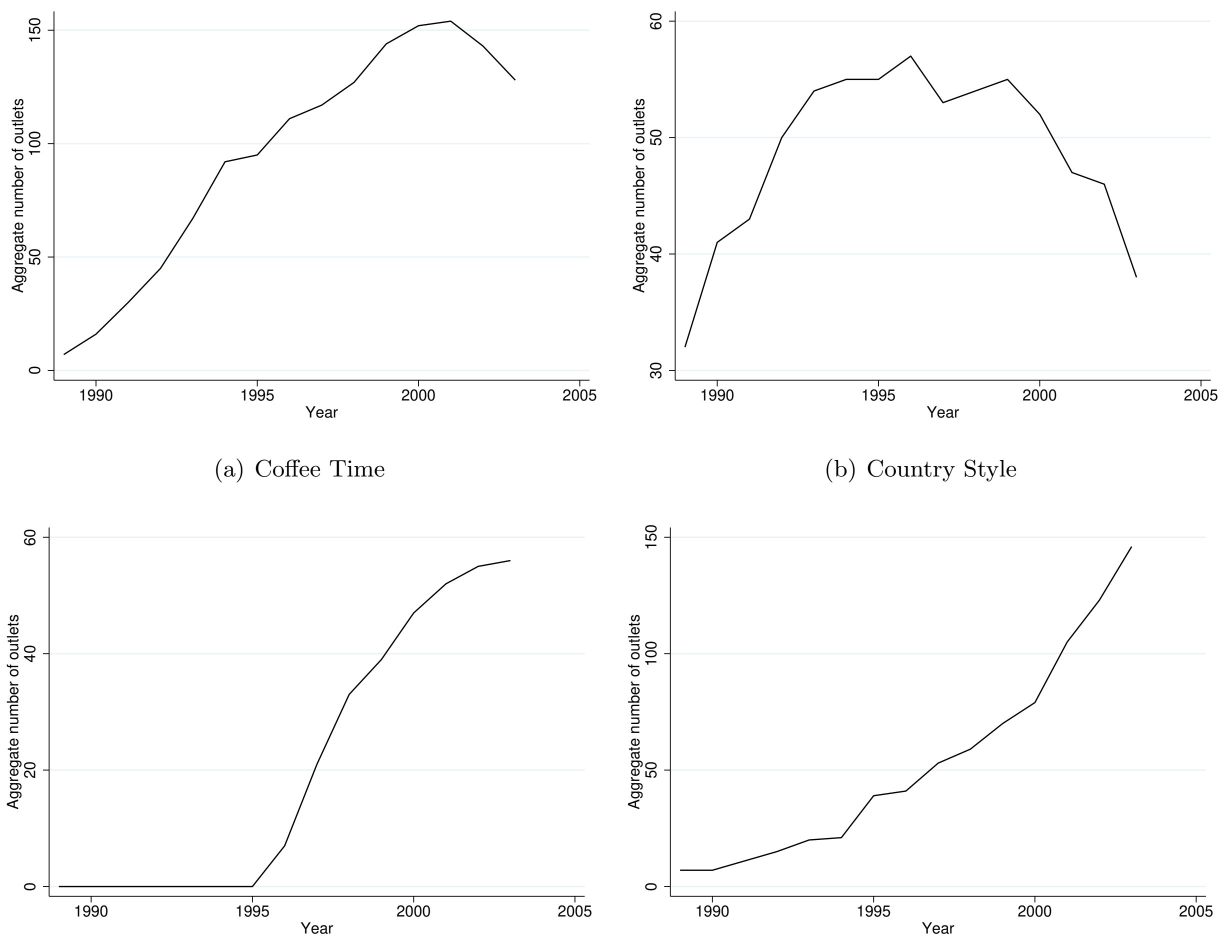
The Canadian coffee chain industry shares many of the ideal features as Igami and Yang's (2016) hamburger chain setting for studying entry and exit. In particular, coffee chains offer a simple form of oligopolistic competition as their products and prices are largely uniform across locations, especially within the same province of Canada. Furthermore, it is likely that coffee stores compete in small geographic markets, which ultimately allows us to study a sufficiently large

Table 1: Number of Outlets per Market

Number of outlets	0	1	2	3+
Coffee Time	1,116	713	219	82
Country Style	1,443	642	45	0
Starbucks	1,903	168	40	19
Tim Hortons	1,522	458	117	33

Figure 1: Distribution of Counts for the Number of Outlets that were Ever Active in Each Market





(a) Coffee Time

(b) Country Style

(c) Starbucks

(d) Tim Hortons

Figure 2: Number of Outlets Across Time

number of geographic markets. Finally, entry and exit are important decisions for all of the coffee store chains. In fact, these chains (e.g., Starbucks) often make investments in location analytics as a way to guide their entry and exit decisions (e.g., Marr, 2018). What makes the coffee chain industry in Canada particularly compelling is the noticeable outlet slowdown and shake-out of some brands, such as Coffee Time and Country Style. Such patterns are less pronounced in the hamburger chain setting as all of the brands experienced somewhat consistent growth over time (e.g., Blevins, Khwaja, and Yang, 2018). For this reason, the coffee chain empirical setting may offer a fruitful opportunity to study the intrinsic motivation, and ultimately, consequences of entry deterrence via investment (i.e., did the dominant chains drive out their competitors?).

4.2 Estimating the Dynamic Game

For the empirical case study, we follow the same model and notation as has been used throughout the earlier sections of the paper. To proceed, we first describe the flow profit specification in Subsection 4.2.1, followed by an outline of the two-step estimation approach we use in Subsection 4.2.2.

4.2.1 Flow Profit Specification

In this sub-section, we offer a few more details about the exact specification used for each firm's flow profits, which are shown below:

$$\Pi_i = n_{it}(\gamma_i^i n_{it} + \sum_{j \neq i}^{J} \gamma_j^i n_{jt} + \gamma_z^i z + \gamma_\omega^i \omega) + a_{it} \cdot 1(a_{it} > 0)\kappa_i^+ + \varepsilon_{it}(a_{it}). \tag{33}$$

The own store effects are captured by the parameter γ_i^i, while the rival store effects are captured by the set of parameters $\{\gamma_j^i\}_{\forall j \neq i}$. If $\gamma_i^i < 0$, then one possible interpretation would be cannibalization effects, while $\gamma_i^i > 0$ might reflect economies of scale or density. Analogously, $\gamma_j^i > 0$ might be indicative of positive spillovers like cultivation of demand for coffee, while $\gamma_j^i < 0$ would be consistent with business-stealing and competition effects. Guided by Table 1, we set the maximum number of outlets a given chain can have in a geographic market to be 2, as it is rare to observe markets with 3 or more outlets belonging to the same chain. With this specification, we can remain agnostic about the sign and magnitude of the strategic interactions, and allow the data to guide us about the extent to which each chain is sensitive to its rivals. It is important to maintain this flexibility as the menu items for each chain do not perfectly overlap, and thus, their products might exhibit some differentiation (i.e., γ_j^i might have a different value for each j and i). Furthermore, varying levels of relative quality across chains (e.g., Vitorino, 2012) may create asymmetry, such that $\gamma^i_j \neq \gamma^j_i$.

In addition to the own and rival store effects, the impact of the observable time-varying market characteristics (e.g., population, income) are summarized by the vector γ^i_z. Furthermore, we incorporate market dummies ω to capture potential heterogeneity across markets; here, γ^i_ω is a set of coefficients for the market dummies; we allow the same market dummy variable to have a different impact on the flow profits of each firm. Finally, the cost of entry is represented by κ^+_i. Here, we normalize the exit scrap value to be 0 as Aguirregabiria and Suzuki (2014) show that the operation or fixed costs, entry costs, and scrap values cannot be separately identified. In our specific setting, the firm-market specific intercepts γ^i_ω are subsumed in the operation/fixed costs. This normalization is similar to the one made in Igami and Yang (2016). In summary, the parameters we need to estimate are those in the average profit function (i.e., γ^i) as well as the entry cost (i.e., κ^+_i). For notational simplicity, we represent all of the structural parameters with $\boldsymbol{\theta} = \{\gamma^i, \kappa^+_i\}$.

To be parsimonious, we classify markets into a small number of types and include market-type dummies to indicate these types in the estimation instead of using 142 market fixed effects. We obtain a flexible approximation for the market fixed effects by first running firm-specific linear fixed effects regressions of store counts on the observable market characteristics, which then allows us to obtain the firm-specific market fixed effects. We then use k-means clustering to group the collection of inferred firm-market fixed effects into k bins; this process allows us to approximate ω. We choose the number of bins to be $k = 8$ based on the elbow method for clustering. That is, the number of clusters that should be chosen is revealed by the "elbow" or "knee" of a fit criterion curve. Finally, the market characteristics - population and income - are assigned into 8 bins as well.

4.2.2 Two-Step Estimation

To estimate the model, we use the two-step algorithm developed by Bajari, Benkard, and Levin (2007). The basic idea of this approach is to approximate the equilibrium CCPs in the first-stage, and then use these approximations to generate approximated in-equilibrium and off-equilibrium value functions via forward simulations. Below, we provide more details about this estimation algorithm.

CCP approximation We first approximate the CCPs using a multinomial logit. This policy function estimation step is meant to approximate each firm's action decision to open a new store

($a_{it} = 1$), close a store ($a_{it} = -1$), or remain at status quo ($a_{it} = 0$), conditional on the state variables, X_t at time t (i.e., existing market structure, market characteristics, market type). With the estimated multinomial logit, we obtain the approximated CCPs for each available action decision across all states, which we will denote with the notation $\hat{\sigma}$.

Forward-simulations With the approximated CCPs from the first stage, we then proceed with the second step of estimation involving forward simulations. With these forward simulations, we can obtain approximated in-equilibrium value functions, which are then compared with perturbed off-equilibrium value functions. The purpose of this step of the estimator is to effectively penalize candidate model estimates that lead to off-equilibrium value functions exceeding in-equilibrium value functions.

To begin the forward simulations, we start with a given initial state (X_1) to initiate the forward simulations for each firm i in market m:

$$\begin{aligned}\bar{V}_{im}(X_1;\sigma,\boldsymbol{\theta}) &= \mathbb{E}\left[\sum_{\tau=1}^{\infty}\beta^{\tau-1}\Pi_{im}(\sigma(X_\tau)),X_\tau;\boldsymbol{\theta})\,\middle|\,X_1,\sigma\right]\\ &\simeq \frac{1}{\bar{K}}\sum_{k=1}^{\bar{K}}\sum_{\tau=1}^{T}\beta^{\tau-1}\Pi_{im}(\sigma(X_\tau^k)),X_\tau^k;\boldsymbol{\theta}). \qquad (34)\end{aligned}$$

Subscript k represents each forward simulation, where $\bar{K}$ paths of length T are simulated in the second stage. The term $\sigma(X_\tau^k)$ denotes a vector of simulated actions based on the approximated policy profile $\hat{\sigma}_i$ from the first stage estimation described earlier. To forward simulate the market characteristics, we assume that population and income evolve according to an AR(1) process.

Using this forward simulation apparatus, we construct two sets of approximated value functions, namely in-equilibrium and off-equilibrium. For the value function approximation, we use the approximated equilibrium CCP ($\hat{\sigma}$). For the off-equilibrium value function approximations, we consider B perturbations of the equilibrium CCP, indexed by $b = 1, ..., B$. We generate these alternative policies by introducing random perturbations to the approximated equilibrium CCPs, whereby these alternative policies are denoted by $\tilde{\sigma}$.

The criterion we use then is described below:

$$h_{imb}(\theta) = \bar{V}_{im}(X_1;\hat{\sigma},\theta) - \bar{V}_{im}(X_1;\tilde{\sigma},\theta), \qquad (35)$$

Here, this criterion describes the difference between the in-equilibrium and off-equilibrium approximated value functions. This criterion should be positive in equilibrium, since off-equilibrium values are lower than discounted profits under equilibrium play. Therefore, this criterion listed below identifies $\boldsymbol{\theta}$ to minimize the violations of the equilibrium requirement:

$$Q(\theta) = \frac{1}{B} \sum_{i} \sum_{m} \sum_{b} (\min\{h_{imb}(\theta), 0\})^2, \tag{36}$$

which is estimated via minimum distance. Our empirical implementation proceeds based on a specification with $\beta = 0.95$, $B = 1,000$, $\varepsilon_{it}(a_{it}) \sim$ i.i.d. extreme value type I, with a location parameter 0 and scale parameter 1, and perturbation of CCPs by a random term with mean/variance distributed as $\varrho \sim N(0, 0.02)$. The standard errors are obtained from bootstrapping across markets, where number of bootstrap draws is 1,000.

4.3 Summary of Estimates

Table 2 provides a summary of the estimated structural parameters. Our main findings from these estimates are as follows. First, higher population markets appear to be attractive for Coffee Time and Country Style, while higher income markets are attractive for Starbucks. We caution over-interpretation of these observable market factors (i.e., what each market type means exactly), as the chains are likely impacted by unobservable market factors as well. For example, market type 0 is attractive to Country Style and Starbucks, market type 1 is attractive for all of the chains except Tim Hortons, market type 2 is attractive for Country Style and Tim Hortons, market type 3 is attractive for Country Style, market type 4 is attractive to Country Style, market type 5 is attractive to Starbucks, market type 6 is attractive to Country Style and Tim Hortons, and finally, market type 7 is attractive to Tim Hortons. While each market type label in itself has no interpretive value as it was obtained via the k-means clustering step, the sign of the market dummy indicators illustrates some common patterns across each chain's profits. To explore some of the subtler patterns in the market type effects across chains, we present Table 3, which shows the cross-chain correlations for these effects. The table highlights positive correlations between Country Style, Coffee Time, and Starbucks, suggesting that these chains might be interested in similar markets, as categorized via their types. In contrast, it appears that Tim Hortons is entering markets that the other three chains are not as interested in, reflected by the negative cross-chain correlations. This pattern is reasonable as many of Tim Hortons' locations focus on drive-thru services, unlike other chains, which focus on walk-ins.

The low entry costs for most of the chains is consistent with the fact that outlets tend to have small physical footprints, and thus, require less overhead upon entry (and while in operation) as

Table 2: Estimated Parameters in Flow Profits for Each Chain

	Coffee Time	Country Style	Starbucks	Tim Hortons
Impact of Coffee Time stores	**-0.034**	**-0.138**	**-0.110**	**0.155**
	(0.010)	(0.013)	(0.014)	(0.017)
Impact of Country Style stores	**-0.111**	**-0.608**	**-0.358**	**-0.294**
	(0.016)	(0.059)	(0.023)	(0.021)
Impact of Starbucks stores	**-0.011**	**-0.173**	**-0.243**	**-0.013**
	(0.004)	(0.011)	(0.030)	(0.005)
Impact of Tim Hortons stores	**0.214**	**0.195**	**0.296**	**0.239**
	(0.023)	(0.017)	(0.025)	(0.021)
Population	0.037	0.084	-0.007	-0.089
	(0.004)	(0.008)	(0.007)	(0.008)
Average income	-0.016	-0.158	0.034	-0.092
	(0.006)	(0.018)	(0.014)	(0.010)
Entry cost	1.351	0.285	0.219	0.325
	(0.020)	(0.029)	(0.023)	(0.036)
Market type 0	-0.115	0.080	0.102	-0.038
	(0.010)	(0.024)	(0.021)	(0.017)
Market type 1	0.149	0.296	0.331	-0.071
	(0.011)	(0.024)	(0.021)	(0.020)
Market type 2	-0.118	0.619	-0.068	0.045
	(0.009)	(0.019)	(0.015)	(0.014)
Market type 3	-0.038	0.052	-0.094	-0.167
	(0.007)	(0.019)	(0.013)	(0.014)
Market type 4	-0.028	0.153	-0.134	-0.186
	(0.007)	(0.012)	(0.009)	(0.022)
Market type 5	-1.008	-0.574	0.092	-0.035
	(0.009)	(0.014)	(0.026)	(0.023)
Market type 6	-0.445	0.041	-0.204	0.037
	(0.015)	(0.022)	(0.024)	(0.012)
Market type 7	-0.211	-0.356	-0.088	0.196
	(0.011)	(0.016)	(0.021)	(0.014)

Note: Bootstrapped standard errors are in parentheses.

Table 3: Cross-Chain Correlations in the Estimated Market Type Effects

	Coffee Time	Country Style	Starbucks	Tim Hortons
Coffee Time	1	0.71605	0.12667	-0.23441
Country Style	.	1	0.025471	-0.23122
Starbucks	.	.	1	-0.13125
Tim Hortons	.	.	.	1

commercial rent is almost always priced per square foot. Since the estimated entry costs also subsume the scrap values, the scrap values are likely small as well. Small scrap values would reflect the fact that unlike the real estate strategies used in chains from other retail sectors (e.g., McDonald's), Starbucks does not own the properties their stores sit on as reflected in the recent news about their attempts to renegotiate all of their lease contracts with landlords (Long, 2020).

Second, the rival store effect is negative for many of the chains, as is the own store effect for Coffee Time, Country Style and Starbucks. The negative own store effects point to potential cannibalization concerns, consistent with other research has uncovered in different retail sectors (e.g., Igami and Yang, 2016). The positive own-store effect for Tim Hortons might be attributed to some type of outlet size spillover (e.g., economies of density), as similarly documented in the fast food industry (Blevins, Khwaja, and Yang, 2018). Note that there are a few cases for which the rival effect is positive, which points to potential complementarities (e.g., market signaling, cultivation of consumer tastes towards coffee store products, pedestrian traffic externalities). Positive spillover effects of a similar nature have also been documented in the fast food industry (e.g., Shen and Xiao, 2014; Yang, 2020), and among big-box department stores (e.g., Vitorino, 2012). Most noticeably, Tim Hortons appears to play a role in cultivating consumer tastes, in an analogous role as Shen and Xiao's (2014) study of KFC in China. This pattern might be consistent with the fact that Tim Hortons has among the largest product selections as compared with the other chains, which provides it some insulation from competition via menu differentiation, while at the same time, cultivating market-level demand for product categories featured on its menu; there are in fact anecdotes of rival coffee chains attempting to mimic menu items that are offered by Tim Hortons, such as breakfast sandwiches (Tedesco, 2013). Furthermore, other chains might not view Tim Hortons as a serious competitive threat, given that a large share of Tim Hortons' businesses are drive-thru services. In addition, its well-known problems with product quality deficiencies and issues with their brand strength (Evans, 2018; Thomas, 2018) reduce the threat and allow its positive effects on other chains to outweigh business stealing concerns.

Looking more closely at the negative rival store effects, we observe that Starbucks, Coffee Time and Country Style appear to be mutual competitors (i.e., their rival effects to one another are both negative). For this reason, these chains will be the main focus of our subsequent analysis of deterrence motives in Section 4.4. Note that Starbucks' sensitivity to competition from Coffee Time and Country Style is consistent with industry anecdotes that Starbucks is most concerned about smaller regional rivals (Taylor, 2017). Moreover, these chains might share some common interest in similar markets, as reflected by our earlier discussion about Table 3. Taken together, these patterns reinforce the value of our agnostic approach towards modeling the interactions between chains. While it is possible to form a prior about the extent to which each chain overlaps with one another in terms of their preferred markets (i.e., whether or not two chains are competitors of one another), our approach is to be as inclusive as possible with respect to the set of chains we include in the model, and let the data ultimately determine whether or not two chains are mutual competitors in the types of markets that they have some shared interest towards.

In summary, estimated model parameters seem to coincide with the observation of rapid growth in Starbucks, alongside the slowing or diminishing presence of regional chains like Coffee Time and Country Style (see Figure 2). The extent to which this increasingly dominant chain is actually motivated to deter and push out its smaller rivals remains an unanswered question, as all we know are that they are mutual competitors and share some common interests in the types of markets they enter. The apparent "aggressive entry" need not necessarily be driven by deterrence motives, as our discussion about the underlying theory would suggest. Thus, we proceed by applying the measure for deterrence motives from our framework to quantify these incentives.

4.4 Quantifying the Deterrence Motives

In this section, we demonstrate how our measure can be used by assessing the role of deterrence motives in the coffee chain industry. We calculate our deterrence measure only on chains that are mutual competitors with one another (i.e., Coffee Time, Country Style and Starbucks), as our measure should only be implemented for firms that are mutually sensitive to business stealing effects (see Section 3.2).

To implement this measure, the forward simulated value functions, choice probabilities, and estimated model primitives are used to construct the key inputs needed to calculate the deterrence measure. Furthermore, the sign of the strategic interaction terms in Table 2 provide us clarity about whether another chain j's choice probabilities are replaced in Equation 19 for chain i (i.e., j exerts business stealing effects on i), or not replace (i.e., j has positive spillovers on i).

As an aside, not performing this replacement for cases when j has positive spillovers retains firms' strategic considerations that do not pertain to entry deterrence. For example, Tim Hortons and Coffee Time are mutually beneficial to each other's profit. Coffee Time may want to enter the market more frequently to induce the entry of Tim Hortons, which in turn increases Coffee Time's profit. This strategic consideration is not entry deterrence. Therefore, by not replacing the choice probabilities of Tim Hortons, we retain Coffee Time's strategic incentives that are not related to deterrence. Furthermore, not performing the replacement for cases when j has positive spillovers will likely lead to more conservative measures for deterrence motives, as the measure would not capture the indirect deterrence motives. For example, Country Style might still have incentives to deter entry of Tim Hortons, as doing so might indirectly deter entry of Country Style's business stealing rivals; these deterrence motives might ultimately overshadow Tim Hortons' positive spillovers on Country Style. We note that our results from this exercise appear virtually invariant to whether or not replacement is performed for a rival with positive spillovers; in sensitivity analysis we conducted, not replacing the choice probabilities of Tim Hortons does yield slightly smaller deterrence measures for Country Style and Starbucks because the indirect deterrence motives of Country Style and Starbucks are not accounted for. The reason for an identical measure for Coffee Time is that its strategic consideration of Tim Hortons generates opposing effects that seem to balance each other out. More specifically, even though Coffee Time is incentivized to attract Tim Hortons into the market, the existence of Tim Hortons can induce other business-stealing rivals (i.e. Country Style and Starbucks) to enter and crowd out the market. Between these options for replacement, we will focus our discussion on the former (i.e. no replacement), as this is the option that makes full use of the information provided in the estimates from Table 2, and thus more likely to be consistent with the actual empirical context.

Figure 3 provides a summary of these measures across the chains. These calculated measures point to the existence of deterrence motives for all of the mutually competitive chains, as the portion that deterrence motives account for out of all entry motives is about 9%, 3%, and 1% for Starbucks, Coffee Time, and Country Style respectively. While these proportions are non-negligible, it also

Figure 3: Deterrence Motives among Chains that are Mutual Competitors

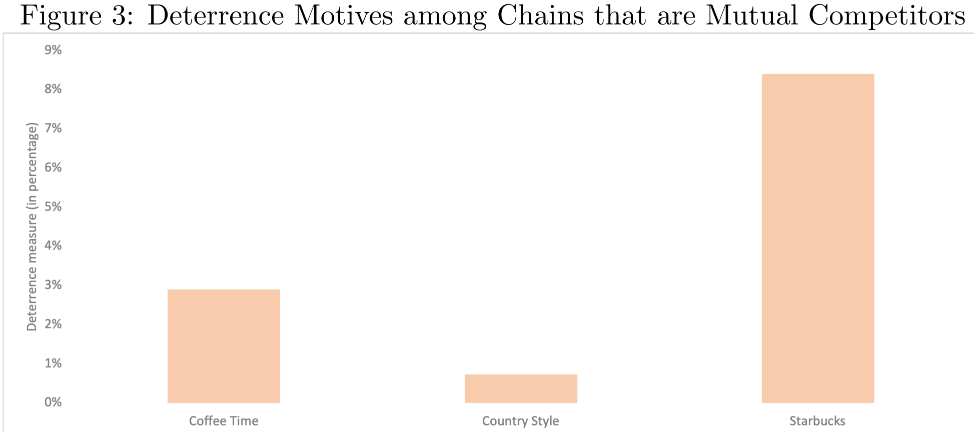
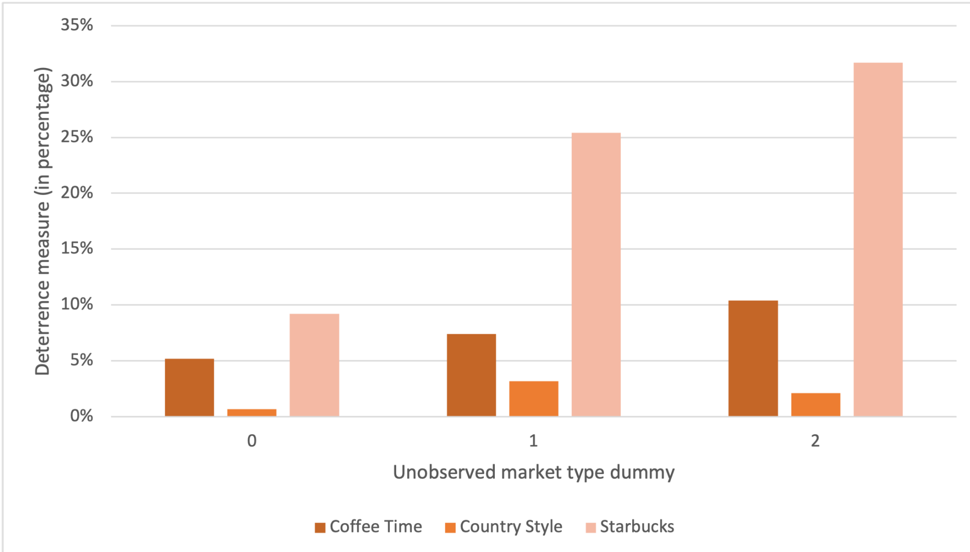


Figure 4: Breakdown of Deterrence Measure Across Different Types of Markets Among Chains that are Mutual Competitors



is apparent that these motives are unlikely the sole force behind entry decisions, which further emphasizes the value of using ratios to quantify them.

As for the heterogeneity in deterrence motives across chains, we see that they are strongest for Starbucks, and noticeably dampened for Coffee Time and Country Style. This finding is important as it shows that the aggressive entry of Starbucks might indeed be driven by deterrence motives. As Starbucks has been singled out as a chain that is likely engaging in deterrence-motivated entry, our calculated measures can provide more targeted policy implications, as it can be broken down across different types of markets. This way, the measure helps flag the types of markets are likely to be subject to deterrence-motivated entry. These insights are provided in Figure 4, where we present each chain's deterrence measure across different markets. Note that this graph does not display the deterrence motives for market types 3, 4, 5, 6, and 7, as they are very close to 0%. From these results, there appears to be noticeable heterogeneity in the deterrence motive across different geographic markets. For example, both Coffee Time and Starbucks has the strongest incentives to deter entry in market type 2, whereas Country Style has the strongest incentives in market type 1.

Taken together, this case study demonstrates the power that our new deterrence measure has at assessing and interpreting retail industry dynamics. The descriptive patterns in Figure 2 pointed to rapid growth of Starbucks and Tim Hortons, coinciding with the downfall of a smaller regional brand Country Style. Furthermore, the estimated parameters in Table 2 help us understand the nature of competition in this industry (i.e., which chains are competitors or complements to one another). In particular, the estimates themselves hint at different drivers behind the rapidly growth of Starbucks and Tim Hortons. For Tim Hortons, expansion may have been driven by economies of density, while strategic considerations towards the rival Country Style may have played a role in Starbucks' expansion efforts. Ultimately, with the help of our deterrence measure, we are able to build some empirical support in the assertion that Starbucks' aggressive and deterrence-motivated expansion was one noticeable factor behind Country Style's shrinking presence. As Starbucks' deterrence motives can be as high as 32% for certain market types (see Figure 4), these motives might be responsible for driving out its rival Country Style in these markets.

5 Conclusion

This paper develops a new framework for quantifying deterrence motives in industry dynamics. We measure these motives using a new measure that is derived by decomposing firms' equilibrium conditions and isolating the benefits from deterrence, while netting out all other entry and investment motives. To demonstrate the practicality of our methodological innovation, we present a comprehensive empirical case study about Canadian coffee chain industry dynamics. The empirical analysis shows that deterrence motives do exist in this industry, and that these motives are asymmetric across the firms, as Starbucks is the chain with the strongest motivation to deter entry; especially so in certain market types. Taken together, our findings suggest that Starbucks' deterrence motives might coincide with its competitor, Country Style, being pushed out of the markets because of Starbucks' aggressive expansion. Through this case study, we demonstrate that our deterrence measure has the capability to flag cases of retail outlet expansion that may be of concern to antitrust authorities or managers doing risk assessments of prospective markets to enter.

This new methodological framework will offer opportunities to pursue targeted approaches towards deterrence-related antitrust issues as it has capabilities of establishing the "who" and "when" dimensions of deterrence. From the manager's perspective, the insights from our measure could be helpful in their *pro forma* risk assessment, so as to identify potentially aggressive chains, and which market types they'll likely focus their aggression on (i.e., prioritizing threats of deterrence). This information would be innovative, as typical environmental scanning done by the managers often involve only the level of existing competition, not anticipated intensity of competition by specific rivals. For example, if antitrust authorities have limited resources to investigate alleged deterrence-motivated behavior, they can use our approach to narrow down the subset of markets and firms that should be further investigated. We believe that this innovation would be in-line with the following identified avenue of improvement for antitrust regulation implementation, namely to establish a general written rule of thumb guidelines for making enforcement decisions on cases, thereby providing "general guidance on the types of enforcement activities to pursue and when" (Office of Inspector General, 2014).

We see a few promising opportunities for this measure to be applied to other research objectives. For example, Fang and Yang (2019) adopt this measure we have developed to examine the relationship between deterrence motives and *ex post* survival in taco chain restaurant dynamics. This type of analysis is feasible, as our measure not only quantifies the existence of deterrence, but can also shed light on the intensity to which deterrence motives are present; thereby, facilitating comparative static analysis. Understanding the relationship between deterrence motives and *ex post* outcomes like failure or bankruptcy might be especially important, given the ongoing discussions that speculate about the factors behind "retail apocalypse" (e.g., Nath, 2020). Furthermore, these patterns can be obtained for each retail sector to assess whether certain industry sectors seem prone to failure among deterrence-motivated firms.

In addition to linking deterrence motives to other market outcomes, we foresee this measure being used in event studies about expansion and investment behavior in light of changes to entry threats. More specifically, our measure might be able to detect noticeable shifts in deterrence motives when an incumbent faces changing threats, from rivals' expansion in neighboring or connected markets (e.g., Goolsbee and Syverson, 2008; Nishida and Yang, 2020), evolving regulations about chain-store entry (e.g., Yang, 2018), merger dynamics and strategy (e.g., Anton et al., 2022; Jeziorski, 2014; Rao, Yu, and Umashankar, 2016), as well as the prevalence of common ownership (e.g., Azar et al., 2018; Backus, Conlon, and Sinkinson, 2020). These changes in the deterrence motives among incumbent firms might reveal whether or not they treat deterrence as a public good that they can free-ride (e.g., Gilbert and Vives, 1986).

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APPENDIX

A Proposition 1 and Proof

PROPOSITION 1

Let j denote a rival of firm i and $-ij$ denote the rest of the rivals. If the following conditions hold, then $C_{1i}(s) > 0$:

$$P_i(1|n_i, n_j, n_{-ij}, z) > P_i(1|n_i, n_j + 1, n_{-ij}, z),$$

$$P_i(-1|n_i, n_j, n_{-ij}, z) < P_i(-1|n_i, n_j + 1, n_{-ij}, z),$$

$$\Upsilon_{\pi_i}(n_i, n_j, n_{-ij}, z'') > \Upsilon_{\pi_i}(n_i, n_j + 1, n_{-ij}, z''), \forall i, j, n_i, n_j, n_{-ij}, z$$

Proposition 1 states that for any firm i, if it is less likely to open a store and more likely to close one when its rivals have one more outlet, and if the NPV of its profits from product competition is higher when its rivals have fewer stores, then component $C_{1i}(s)$ is positive. These conditions in the proposition are fairly common in the real world. As long as there are competitive effects between firms and there is some level of commitment to entry, i.e. firms' entry costs are larger than their scrap values, these conditions are likely to hold. The proof is as follows:

Proof We prove component $C_{1i}(s)$ in equation 17 is greater than 0 by mathematical induction. We show that if $C_{1i}(s) > 0$ holds for $N = k$ firms, then it holds for $N = k + 1$ firms, and by induction, it holds for any $N \geq 2$. We start the proof for the case where $N = 2$. With only two firms, denoted by i and j, we can expand $C_{1i}(s)$ as follows by incorporating the condition $\sum_{a_j} P_j(a_j|\boldsymbol{s}) = 1, \forall j, \boldsymbol{s}$:

$$C_{1i}(s) = \beta \sum_{z''} f(z''|z') \left(\sum_{k=-1}^{1} P_i(k|s'_{+1}) D_{j2} \right), \text{ where} \tag{37}$$

$$\begin{aligned} D_{j2} = &\sum_{a'_j} \left(P_j(a'_j|s'_{+1}) - P_j(a'_j|s'_0) \right) \Upsilon_{\pi_i}(n_i + 1 + k, n_{-i} + a_j + a'_j, z'') \\ = &\left(P_j(1|s'_0) - P_j(1|s'_{+1}) \right) \left(\Upsilon_{\pi_i}(n_i + 1 + k, n_{-i} + a_j + 0, z'') - \Upsilon_{\pi_i}(n_i + 1 + k, n_{-i} + a_j + 1, z'') \right) \\ &+ \left(P_j(-1|s'_{+1}) - P_j(-1|s'_0) \right) \left(\Upsilon_{\pi_i}(n_i + 1 + k, n_{-i} + a_j - 1, z'') - \Upsilon_{\pi_i}(n_i + 1 + k, n_{-i} + a_j + 0, z'') \right) \end{aligned}$$

As can be seen from equation 37, as long as $D_{j2} > 0$, then $C_{1i}(s) > 0$. Under the conditions outlined in Proposition 1, the following inequalities must hold: $P_j(1|s'_0) > P_j(1|s'_{+1})$, $P_j(-1|s'_{+1}) > P_j(-1|s'_0)$, $\Upsilon_{\pi_i}(n_i + 1 + k, n_{-i} + a_j + 0, z'') > \Upsilon_{\pi_i}(n_i + 1 + k, n_{-i} + a_j + 1, z'')$ and $\Upsilon_{\pi_i}(n_i + 1 + k, n_{-i} + a_j - 1, z'') > \Upsilon_{\pi_i}(n_i + 1 + k, n_{-i} + a_j + 0, z'')$. These inequalities imply that $D_{j2} > 0$. Therefore, $C_{1i}(s) > 0$ for $N = 2$.

We now show that $C_{1i}(s) > 0$ when $N = 3$. The proof uses results $D_{j2} > 0$ from the previous case. Let j and l denote the two rival firms, we can now formulate $C_{1i}(s)$ as

$$C_{1i}(s) = \beta \sum_{z''} f(z''|z') \left(\sum_{k=-1}^{1} P_i(k|s'_{+1}) D_{-i3} \right), \text{ where} \tag{38}$$

$$D_{-i3} = \sum_{a'_{-i}} \left(P_{-i}(a'_{-i}|s'_{+1}) - P_{-i}(a'_{-i}|s'_0)\right) \Upsilon_{\pi_i}(n_i + 1 + k, n_{-i} + a_{-i} + a'_{-i}, z'')$$

$$= \sum_{a'_j} P_j(a'_j|s'_{+1}) \widetilde{D_{l2}} + \sum_{a'_l} P_l(a'_l|s'_0) \widetilde{D_{j2}}, \text{ where}$$

$$\widetilde{D_{l2}} = \sum_{a'_l} \left(P_l(a'_l|s'_{+1}) - P_l(a'_l|s'_0)\right) \Upsilon_{\pi_i}(n_i + 1 + k, n_{-i} + a_{-i} + (a'_j, a'_l), z'')$$

$$\widetilde{D_{j2}} = \sum_{a'_j} \left(P_j(a'_j|s'_{+1}) - P_j(a'_j|s'_0)\right) \Upsilon_{\pi_i}(n_i + 1 + k, n_{-i} + a_{-i} + (a'_j, a'_l), z'')$$

As can be seen, D_{-i3} contains two elements $\widetilde{D_{l2}}$ and $\widetilde{D_{j2}}$, both of which have very similar function forms as D_{j2}. Expanding these two terms the same way as we did for D_{j2}, it can be easily shown that $\widetilde{D_{l2}} > 0$ and $\widetilde{D_{j2}} > 0$. Therefore, $C_{1i}(s) > 0$ when $N = 3$.

For the case when $N = 4$, the proof uses results from the previous two cases. The proof for $N = 4$ generalizes the proof for any $N \geq 4$. Let j denote one of the rival firms, and let $-ij$ denote the rest of the rival firms. With a sleight of hand, $C_{1i}(s)$ can be expanded into

$$C_{1i}(s) = \beta \sum_{z''} f(z''|z') \left(\sum_{k=-1}^{1} P_i(k|s'_{+1}) D_{-i4} \right), \text{ where} \tag{39}$$

$$D_{-i4} = \sum_{a'_j} P_j(a'_j|s'_{+1}) \widetilde{D_{-ij3}} + \sum_{a'_{-ij}} P_{-ij}(a'_{-ij}|s'_0) \widetilde{D'_{j2}}$$

$$\widetilde{D_{-ij3}} = \sum_{a'_{-ij}} \left(P_{-ij}(a'_{-ij}|s'_{+1}) - P_{-ij}(a'_{-ij}|s'_0)\right) \Upsilon_{\pi_i}(n_i + 1 + k, n_{-i} + a_{-i} + (a'_j, a'_{-ij}), z'')$$

$$\widetilde{D'_{j2}} = \sum_{a'_j} \left(P_j(a'_j|s'_{+1}) - P_j(a'_j|s'_0)\right) \Upsilon_{\pi_i}(n_i + 1 + k, n_{-i} + a_{-i} + (a'_j, a'_{-ij}), z'')$$

As can be seen, D_{-i4} contains $\widetilde{D_{-ij3}}$ and $\widetilde{D'_{j2}}$, which are very similar to D_{-i3} and D_{j2} respectively. Using the expansion from the previous proofs, we can easily show that $\widetilde{D_{-ij3}} > 0$ and $\widetilde{D'_{j2}} > 0$. Therefore, $C_{1i}(s) > 0$ when $N = 4$.

For any $N > 4$, $C_{1i}(s)$ can be written the same way as equation 39. For $N = k$, the proof then uses the results from those cases with $N = k - 1$ and $N = 2$. Therefore, as long as the conditions stated in Proposition 1 hold, $C_{1i}(s) > 0$ for any firm i at any state s. Q.E.D. $\square$

B Decomposition in the Investment Setting

As discussed in the main text, we focus on those future states at which the rivals have the option to enter or exit the market (i.e., firm i's rival j's next period state is either $n'_j = 0$ or $n'_j = 1$. Below, we provide decomposition details about the two main cases, and we define entry deterrence motives for one period in Subsection B.1 and those for all periods in Subsection B.2.

B.1 Deterrence Motives from Affecting Rivals' Actions in One Period

Case 1 The decomposition for this first case where $n'_j = 0$ is meant to capture firm i's long-run benefit from deterring the entry of firm j in the next period. We can proceed with the decomposition for this case as follows. To be clear on terminology, we call $C_{1i}(s)$ in the investment setting as firm i's strategic motives at state s. Then for any $j \neq i$, firm i's strategic motives that involve $n'_j = 0$ are

$$\begin{aligned}
&\beta \textstyle\sum_{z''} f(z''|z')\left\{\sum_{k=-1}^{1}\sum_{a'_{-ij}}\sum_{a'_j} P_i(k|s'_{+10})\left\{P_{-ij}(a'_{-ij}|s'_{+10})P_j(a'_j|s'_{+10}) - P_{-ij}(a'_{-ij}|s'_{00})P_j(a'_j|s'_{00})\right\}\Upsilon_{\pi_i}(n_i+1+k, n'_{-i}+a'_{-i}, z'')\right\}\\
=&\beta \textstyle\sum_{z''} f(z''|z')\left\{\sum_{k=-1}^{1}\sum_{a'_{-ij}}\sum_{a'_j} P_i(k|s'_{+10})P_j(a'_j|s'_{00})\left(P_{-ij}(a'_{-ij}|s'_{+10}) - P_{-ij}(a'_{-ij}|s'_{00})\right)\Upsilon_{\pi_i}(n_i+1+k, n'_{-i}+a'_{-i}, z'')\right\}\\
&+\beta \textstyle\sum_{z''} f(z''|z')\left\{\sum_{k=-1}^{1}\sum_{a'_{-ij}}\sum_{a'_j} P_i(k|s'_{+10})P_{-ij}(a'_{-ij}|s'_{+10})\left(P_j(a'_j|s'_{+10}) - P_j(a'_j|s'_{00})\right)\Upsilon_{\pi_i}(n_i+1+k, n'_{-i}+a'_{-i}, z'')\right\}, \qquad (40)
\end{aligned}$$

where $s'_{+10} = (n_i + 1, n'_{-ij}, n'_j = 0, z'')$ and $s'_{00} = (n_i, n'_{-ij}, n'_j = 0, z'')$.

The 2nd line of equation 40 is firm i' strategic motives relating to other firms, whereas the last line is those relating to only firm j. Given that at state $n'_j = 0, \forall j \neq i$, firm j is limited to two actions of $\{1, 0\}$, the entire last line, denoted by $CI^e_{1i}(s)$, captures firm i's motive to deter the entry of firm j. To see this more clearly, we can rearrange the last line by applying the relationship $P_j(0|s) + P_j(1|s) = 1, \forall s = (n_i, n_{-ij}, n_j = 0, z)$:

$$CI^e_{1i}(s) =$$

$$\beta \textstyle\sum_{z''} f(z''|z')\left\{\sum_{k=-1}^{1}\sum_{a'_{-ij}}\sum_{a'_j} P_i(k|s'_{+10})P_{-ij}(a'_{-ij}|s'_{+10})\left(P_j(1|s'_{00}) - P_j(1|s'_{+10})\right)\left(\Upsilon_{\pi_i}(n_i+1+k, n'_{-ij}+a'_{-ij}, 0, z'') - \Upsilon_{\pi_i}(n_i+1+k, n'_{-ij}+a'_{-ij}, 1, z'')\right)\right\} \qquad (41)$$

Under the conditions outlined in Proposition 1, $P_j(1|s'_{00}) > P_j(1|s'_{+10})$ and $\Upsilon_{\pi_i}(n_i+1+k, n'_{-ij}+a'_{-ij}, 0, z'') > \Upsilon_{\pi_i}(n_i+1+k, n'_{-ij}+a'_{-ij}, 1, z'')$. Therefore, the entire last line of equation 41 is greater than 0, which reflects the long-run benefit that firm i enjoys from deterring the entry of firm j in the next period.

Case 2 The decomposition for this second case is meant to capture firm i's long-run benefit from inducing the exit of firm j. If $n'_j = 1, \forall j \neq i$, a similar decomposition as in the first case applies. For simplicity, we omit $\beta \sum_{z''} f(z''|z')$ in the decomposition, and write firm i's strategic motives for firm j only as

$$\sum_{k=-1}^{1} \sum_{a'_{-ij}} \sum_{a'_j} P_i(k|s'_{+11}) P_{-ij}(a'_{-ij}|s'_{+11}) \big(P_j(a'_j|s'_{+11}) - P_j(a'_j|s'_{01})\big) \Upsilon_{\pi_i}(n_i+1+k, n'_{-i}+a'_{-i}, z''), \tag{42}$$

where $s'_{+11} = (n_i + 1, n'_{-ij}, n'_j = 1, z'')$ and $s'_{01} = (n_i, n'_{-ij}, n'_j = 1, z'')$. Since at $n'_j = 1$, firm j has 3 action choices: $\{1, 0, -1\}$ (i.e. investment, do nothing, and exiting). Firm i's motive to induce the exit of firm j requires further decomposition of the term in expression 42. By applying the constraint $P_j(1|s) + P_j(0|s) + P_j(-1|s) = 1, \forall s$, we can rewrite the above term as follows:

$$\begin{aligned}
&\sum_{k=-1}^{1} \sum_{a'_{-ij}} \sum_{a'_j} P_i(k|s'_{+11}) P_{-ij}(a'_{-ij}|s'_{+11}) \big(P_j(a'_j|s'_{+11}) - P_j(a'_j|s'_{01})\big) \Upsilon_{\pi_i}(n_i+1+k, n'_{-i}+a'_{-i}, z'') \\
= &\sum_{k=-1}^{1} \sum_{a'_{-ij}} \sum_{a'_j} P_i(k|s'_{+11}) P_{-ij}(a'_{-ij}|s'_{+11}) \big(P_j(1|s'_{+11}) - P_j(1|s'_{01})\big) \big(\Upsilon_{\pi_i}(n_i+1+k, n'_{-ij}+a'_{-ij}, 2, z'') - \Upsilon_{\pi_i}(n_i+1+k, n'_{-ij}+a'_{-ij}, 1, z'')\big) \\
+ &\sum_{k=-1}^{1} \sum_{a'_{-ij}} \sum_{a'_j} P_i(k|s'_{+11}) P_{-ij}(a'_{-ij}|s'_{+11}) \big(P_j(-1|s'_{+11}) - P_j(-1|s'_{01})\big) \big(\Upsilon_{\pi_i}(n_i+1+k, n'_{-ij}+a'_{-ij}, 0, z'') - \Upsilon_{\pi_i}(n_i+1+k, n'_{-ij}+a'_{-ij}, 1, z'')\big)
\end{aligned} \tag{43}$$

Based on Proposition 1, all three lines of equation 43 are positive. The 2nd line of the equation pertains to firm i's motive to discourage firm j's investment; that is, stopping it from improving quality. The last line involves firm i's motive to induce the exit of firm j. Since firm j is more likely to exit when firm i is at a higher quality level, $P_j(-1|s'_{+11}) > P_j(-1|s'_{01})$. Therefore, the entire last line provides us the return to firm i's values by inducing the exit of firm j. Let $CI^x_{1i}(s)$ denote the last line with $\beta \sum_{z''} f(z''|z')$, then

$$\begin{aligned}
&CI^x_{1i}(s) = \\
&\beta \sum_{z''} f(z''|z') \left\{ \sum_{k=-1}^{1} \sum_{a'_{-ij}} \sum_{a'_j} P_i(k|s'_{+11}) P_{-ij}(a'_{-ij}|s'_{+11}) \big(P_j(-1|s'_{+11}) - P_j(-1|s'_{01})\big) \big(\Upsilon_{\pi_i}(n_i+1+k, n'_{-ij}+a'_{-ij}, 0, z'') - \Upsilon_{\pi_i}(n_i+1+k, n'_{-ij}+a'_{-ij}, 1, z'')\big) \right\}
\end{aligned} \tag{44}$$

Let $CI^e_{2i}(s)$ and $CI^x_{2i}(s)$ be the respective counterparts of $CI^e_{1i}(s)$ and $CI^x_{1i}(s)$ in equation 12. Then Definition 3 states the one-period deterrence motives in the investment setting.

DEFINITION 3

In the investment setting,

$\beta \sum_{a_{-i}} \sum_{z'} P_{-i}(a_{-i}|s) f(z'|z) CI^e_{1i}(s)$ and $\beta \sum_{a_{-i}} \sum_{z'} P_{-i}(a_{-i}|s) f(z'|z) CI^e_{2i}(s)$ are firm i's motives at state (n_i, n_{-i}, z)

to **deter the entry** of firm j in the next period;

$\beta \sum_{a_{-i}} \sum_{z'} P_{-i}(a_{-i}|s) f(z'|z) CI^x_{1i}(s)$ and $\beta \sum_{a_{-i}} \sum_{z'} P_{-i}(a_{-i}|s) f(z'|z) CI^x_{2i}(s)$ are firm i's motives at state (n_i, n_{-i}, z) to **induce the exit** of firm j in the next period.

Both the derivations and Definition 3 specify entry deterrence motives of firm i for deterring firm j only. The motives for deterring two or more firms at the same time can be derived analogously. Similar to Definition 1 in the retail setting, the motives in Definition 3 are from deterring rivals in *one* period, but not for *all* future periods. By following a similar derivation process as that in the retail setting, we can construct a $\widetilde{\Upsilon}_{\pi_i}(\cdot)$ term, where rivals' entry and exit (not investment) probabilities are held constant across firm i's states. We discuss the construction of this term and the definition of enter deterrence motives for *all* periods and *all* firms in Subsection B.2.

B.2 Deterrence Motives from Affecting Rivals' Actions in All Future Periods

As shown in equation 41 and equations 44, one can remove the entry deterrence motives in an investment model for both Cases 1 and 2 while maintaining other aspects of the strategic motives. To remove the entry deterrence motives, we can simply set the following equalities:

$$P_j(0|n_i + 1, n'_{-ij}, 0, z'') = P_j(0|n_i, n'_{-ij}, 0, z''), \forall n_i, n'_{-ij}, z'', j \tag{45}$$

$$P_j(-1|n_i + 1, n'_{-ij}, 1, z'') = P_j(-1|n_i, n'_{-ij}, 1, z''), \forall n_i, n'_{-ij}, z'', j \tag{46}$$

These relationships imply that

$$P_j(0|n_i + 1, n'_{-ij}, 0, z'') = P_j(0|0, n'_{-ij}, 0, z''), \forall n_i, n'_{-ij}, z'', j \tag{47}$$

$$P_j(-1|n_i + 1, n'_{-ij}, 1, z'') = P_j(-1|0, n'_{-ij}, 1, z''), \forall n_i, n'_{-ij}, z'', j \tag{48}$$

That is, for any firm j, its CCP at state $(n_i+1, n'_{-ij}, 0, z'')$ should be replaced by that at state $(0, n'_{-ij}, 0, z'')$, where firm i is not in the market. And firm j's CCP of exiting at state $(n_i+1, n'_{-ij}, 1, z'')$ should be replaced by that at state $(0, n'_{-ij}, 1, z'')$. Note that the conditions in the investment setting are not as strict as those in the retail setting, as shown in Subsection 3.2. In the investment setting, the conditions need to hold for only specific states, $n'_j = 0$ and $n'_j = 1$, whereas in the retail setting, the conditions need to hold for all states.

Following a similar procedure as that in the retail setting, we can construct a term $\widetilde{\Upsilon}_{\pi_i}(\cdot)$, in which *all* rival firms' CCPs of exiting and entering the market are fixed at those where firm i is not in the market.

$\widetilde{\Upsilon}_{\pi_i}(\cdot)$ then reflects firm i's NPV of profits if the entry and exit decisions of *all* rivals in *all* future periods are held constant, although their investment decisions are not. Let $\widetilde{\mathbf{\Upsilon}}_{\pi_i}$ be the vector that stacks $\widetilde{\Upsilon}_{\pi_i}(\cdot)$ by state. Then we have

$$\widetilde{\mathbf{\Upsilon}}_{\pi_i} \equiv (I - \beta \widetilde{F})^{-1} \boldsymbol{\pi}_i, \tag{49}$$

where $\widetilde{F}$ is formed by replacing $P_j(a_j|n_i+1, n'_{-ij}, 0, z'')$ with $P_j(a_j|0, n'_{-ij}, 0, z''), \forall a_j \in \{1, 0\}, j \neq i$, and $P_j(-1|n_i+1, n'_{-ij}, 1, z'')$ with $P_j(-1|0, n'_{-ij}, 1, z''), \forall j \neq i$, in the transition matrix F. Note that replacing $P_j(-1|n_i+1, n'_{-ij}, 1, z'')$ with $P_j(-1|0, n'_{-ij}, 1, z'')$ leaves two other probabilities $P_j(1|n_i+1, n'_{-ij}, 1, z'')$ and $P_j(0|n_i+1, n'_{-ij}, 1, z'')$ undetermined because although they need to add up to $1 - P_j(-1|0, n'_{-ij}, 1, z'')$, their exact values can have a range. To set values for these two probabilities, we prorate them for simplicity. Specifically, we replace $P_j(0|n_i+1, n'_{-ij}, 1, z'')$ with $\widetilde{P}_{-i}(1|n_i+1, n'_{-ij}, 1, z'')$ and $P_j(1|n_i+1, n'_{-ij}, 1, z'')$ with $\widetilde{P}_{-i}(0|n_i+1, n'_{-ij}, 1, z'')$:

$$\widetilde{P}_{-i}(1|n_i+1, n'_{-ij}, 1, z'') = P_{-i}(1|n_i+1, n'_{-ij}, 1, z'') \frac{(1 - P_{-i}(-1|0, n'_{-ij}, 1, z''))}{(1 - P_{-i}(-1|n_i+1, n'_{-ij}, 1, z''))}, \tag{50}$$

$$\widetilde{P}_{-i}(0|n_i+1, n'_{-ij}, 1, z'') = P_{-i}(0|n_i+1, n'_{-ij}, 1, z'') \frac{(1 - P_{-i}(-1|0, n'_{-ij}, 1, z''))}{(1 - P_{-i}(-1|n_i+1, n'_{-ij}, 1, z''))} \tag{51}$$

Now, similar to what we have done for the retail setting, we can decompose $V_i(n_i+1, n_{-i}+a_{-i}, z') - V_i(n_i, n_{-i}+a_{-i}, z')$ as

$$V_i(n_i+1, n_{-i}+a_{-i}, z') - V_i(n_i, n_{-i}+a_{-i}, z') = A_{1i}(s) + BAI_{1i}(s) + CAI_{1i}(s), \text{ where} \tag{52}$$

$$A_{1i}(s) = \Upsilon_{eve_i}(s'_{+1}) - \Upsilon_{eve_i}(s'_0) \tag{53}$$

$$BAI_{1i}(s) = \widetilde{\Upsilon}_{\pi_i}(s'_{+1}) - \widetilde{\Upsilon}_{\pi_i}(s'_0) \tag{54}$$

$$CAI_{1i}(s) = (\Upsilon_{\pi_i}(s'_{+1}) - \Upsilon_{\pi_i}(s'_0)) - \left(\widetilde{\Upsilon}_{\pi_i}(s'_{+1}) - \widetilde{\Upsilon}_{\pi_i}(s'_0)\right) \tag{55}$$

Again $CAI_{1i}(s)$ is the gain in firm i's NPV of profits from affecting the entry and exit decisions of *all* firms in *all* future periods. It is the deterrence motives for all periods in the investment setting. Let $CAI_{2i}(s)$ denote the counterpart of $CAI_{1i}(s)$ in equation 12. Then Definition 4 states the all-period deterrence motives in the investment setting.

DEFINITION 4

In the investment setting, $\beta \sum_{a_{-i}} \sum_{z'} P_{-i}(a_{-i}|s) f(z'|z) CAI_{1i}(s)$ and $\beta \sum_{a_{-i}} \sum_{z'} P_{-i}(a_{-i}|s) f(z'|z) CAI_{2i}(s)$ are firm i's deterrence motives at state (n_i, n_{-i}, z) from affecting *all* rivals' entry and exit decisions in *all* future periods.

B.3 Terms Used in the Deterrence Measure Under the Investment Setting

As mentioned in Section 3.3, the measure of deterrence motives in the investment setting depends on four important terms, $\widetilde{BAI}_{1i}(s)$, $\widetilde{BAI}_{2i}(s)$, $\widetilde{CAI}_{1i}(s)$ and $\widetilde{CAI}_{2i}(s)$. Their functional forms are

$$\widetilde{BAI}_{1i}(s) = \beta \sum_{a_{-i}} \sum_{z'} P(a_{-i}|s) f(z'|z) \left(\widetilde{\Upsilon}_{\pi_i}(s'_{+1}) - \widetilde{\Upsilon}_{\pi_i}(s'_0) \right)$$

$$\widetilde{BAI}_{2i}(s) = \beta \sum_{a_{-i}} \sum_{z'} P(a_{-i}|s) f(z'|z) \left(\widetilde{\Upsilon}_{\pi_i}(s'_0) - \widetilde{\Upsilon}_{\pi_i}(s'_{-1}) \right)$$

$$\widetilde{CAI}_{1i}(s) = \beta \sum_{a_{-i}} \sum_{z'} P(a_{-i}|s) f(z'|z) \left(\left(\Upsilon_{\pi_i}(s'_{+1}) - \Upsilon_{\pi_i}(s'_0) \right) - \left(\widetilde{\Upsilon}_{\pi_i}(s'_{+1}) - \widetilde{\Upsilon}_{\pi_i}(s'_0) \right) \right)$$

$$\widetilde{CAI}_{2i}(s) = \beta \sum_{a_{-i}} \sum_{z'} P(a_{-i}|s) f(z'|z) \left(\left(\Upsilon_{\pi_i}(s'_0) - \Upsilon_{\pi_i}(s'_{-1}) \right) - \left(\widetilde{\Upsilon}_{\pi_i}(s'_0) - \widetilde{\Upsilon}_{\pi_i}(s'_{-1}) \right) \right)$$

C Proof of Expected Utility Conditional on Choice Being Equal Across Choice

The proof is based on Victor Aguirregabiria's 2010 notes, titled "Some Useful Properties and Formulas for Random Utility Models with Logit, Nested Logit, and Ordered Nested Logit Stochastic Components." Consider any discrete choice random utility model, where a denotes a choice, A the set of choices, J the number of choices in the set, u_a utility associated with choice a, $u = (u_1, u_2, \ldots, u_J)$ the vector of choice-specific utilities, ε_a the random shock associated with choice a, and a^* the optimal choice. Then

$$a^* = \underset{a \in A}{\operatorname{argmax}} \{u_a + \varepsilon_a\} \tag{56}$$

Let $e(a, u) = u_a + E(\varepsilon_a | u, a^* = a)$ be the expected utility conditional on action a being chosen, and let v^* represents the maximum utility every time the agent makes a choice. Then the following is true:

$$\begin{aligned} e(a, u) &= u_a + E(\varepsilon_a | u, v^* = u_a + \varepsilon_a) \\ &= u_a + E(v^* - u_a | u) \\ &= E(v^* | u), \forall a \in A \end{aligned} \tag{57}$$

Given that $E(v^*|u)$ does not depend on the choice, it has to be true that $e(a, u) = e(a', u), \forall a, a' \in A$. Q.E.D.