Risky Preemptive Investment*

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Abstract

Our study characterizes the riskiness of strategic firm investment aimed at deterring competitors from entering markets. We develop the dynamic oligopoly theoretical framework for assessing the relationship between preemptive motives and survival. With monthly data about fast casual taco chains in Texas, we demonstrate that competitive conditions might be informative about the riskiness of a firm's aggressive entry strategies. In contrast, cost conditions do not appear to impact this relationship between preemptive motives and survival.

Keywords: Dynamic Oligopoly Games; Entrepreneurship; Establishment Entry; Deterrence; Firm Investment; Market Power; Product Market Competition; Retail Sector

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"He who knows when he can fight and when he cannot, will be victorious."

— Sun Tzu (*The Art of War*)

1 Introduction

Firms may have strong incentives to engage in preemptive investment when faced with entry threats. Such behavior is speculated to be prevalent in product market competition, such as retail.[1] Although it might be conventional to assume that this aggressive investment strategy is optimal *ex ante*, the consequences (e.g., establishment closures, firm failure, bankruptcy) of such strategies remain a mystery. This question seems especially pertinent in light of oft-mentioned news about the "retail apocalypse," that is partly characterized by a large exodus of retail establishments.[2] Our research explores the possibility that aggressive deterrence-motivated investment has some connection to *ex post* incidences of firm failure. Establishing whether or not (and when) this connection exists might ultimately be helpful for characterizing the riskiness of a firm's apparent aggressive deterrence-motivated investment strategies. Understanding these risks might help counterbalance the apparent over-emphasis on aggressive growth in the retail industry among capitalists that reward such strategies (Fisher et al. 2017).[3]

We develop a new theoretical framework for studying this postulated connection between preemptive investment and *ex post* riskiness. This framework is developed as a means to support data-driven simulation analysis that can ultimately be applied to specific industry sectors. Our framework revolves around a dynamic oligopoly game of investment. This theoretical framework provides us structured guidance about how to construct measures

[1] See, for example, "Corporate sardines," *The Economist*, May 3, 2014. One may also speculate that the incentive to deter entry via aggressive firm expansion might be consistent with patterns of increased firm scope and scale over time (Hoberg and Phillips 2022).

[2] See, for example, "The retail apocalypse isn't over: it's coming back to bite department stores, experts warn," *Business Insider*, December 15, 2022.

[3] As a matter of semantics, we interpret the risk as a potential financial loss inherent in an investment decision, as opposed to the degree of uncertainty or volatility.

pertaining to deterrence motives along with *ex post* survival. Establishing a measure that quantifies deterrence motives is non-trivial, as these motives are never directly observed as raw data. The basic intuition behind this quantification exercise is to isolate the firm's expected value from its bolstered *future* market power via deterrence *because* of its aggressive investments *today*.

With this framework in place, we empirically analyze firm investment decisions for the taco fast casual sector in Texas (from 1993 to 2015). This setting allows us to observe the strategic interactions between Taco Cabana (the incumbent) versus Chipotle's (the entrant). Monthly data about their entry behavior and sales, along with detailed proxies for market size (e.g., population, income, daily traffic, urban features like nearby interstate) is used to fit our theoretical model to the data.[4] The fitted model is then used to conduct a series of simulations as a means to calculate the deterrence motivation and survival metrics that we derived theoretically. These simulations are carried out over a range of model primitives that affect the competition between firms. This way, we are able to explore the relationship between deterrence motives and *ex post* survival in the space of the model primitives that reflect competition conditions and sunk costs.

This analysis reveals potential non-monotonic relationships between the competitiveness of a potential entrant and the extent to which preemptive investments will harm *ex post* survival - the failure risks linked to preemptive entry appear most muted when the entrant is not too strong such that preemptive efforts have no impact, and at the same time, not too weak such that preemptive efforts are not even needed to deter the entrant. In contrast, sunk costs of entry do not appear to impact the relationship between deterrence motives and survival, as survival rates appear similar regardless of whether investment strategies are preemptive or not. Taken together, our results establish the properties for the risk profile of aggressive investment strategies, as they seem to be largely shaped by competition, and not

[4] The dynamics model is estimated using the two-step approach by Bajari et al. (2007). We refer the reader to Aguirregabiria et al. (2021) and Berry and Compiani (2021) for an overview of recently developed structural econometric methods for estimating dynamic games.

sunk cost, conditions.

Theoretical research on deterrence-motivated investment strategies has a long history. The original theoretical contributions emerged from Dixit (1980), Fudenberg and Tirole (1985), Judd (1985), Eaton and Ware (1987), Eaton and Lipsey (1979), and Schmalensee (1978). In particular, this research has primarily explored the plausibility of aggressive investment as a means to credibly deter competitor entry. Empirical work on aggressive investment has focused on decomposing early mover advantages or disadvantages (Blevins et al. 2018, Boulding and Christen 2003, Van Heerde et al. 2010) as well as the responses by incumbents to the threats of (product) entry (Cookson 2017, 2018, Ellison and Ellison 2011, Goolsbee and Syverson 2008, Hoberg et al. 2014, Nishida and Yang 2020, Parise 2018, Seamans 2012, 2013, Uzunca and Cassiman 2023, West 1981). More recently, researchers have developed state-of-the-art empirical methods to carefully quantify deterrence motives (Chicu 2013, Fang and Yang 2022, 2023, Gil et al. 2021, Hünermund et al. 2014, Igami and Yang 2016, Zheng 2016).[5] We contribute towards this literature by characterizing the *ex post* consequences of deterrence-motivated investment.

Our work also contributes to the literature about industry dynamics that studies cross-sectional differences in firm turnover rates and investment failure (Asplund and Nocke 2006, Chi 2022, Collard-Wexler 2013, Dunne et al. 1989, Fan and Xiao 2015, Hopenhayn 1992, Jovanovic 1982, Kerr and Nanda 2009, Miao 2005, Srinivasan et al. 2013, Yost et al. 2021, Shaked and Orelowitz 2017). We complement this extensive literature by offering new insights of the possibility that these differences might in part be linked to strategic considerations, such as preemptive motives.

Finally, an active area of research in corporate finance and strategy focuses on the consequences of (dynamic) product market competition (He et al. 2021, Hou and Robinson 2006, Hsu et al. 2021, Ma 2019, Tookes 2008, Spiegel and Tookes 2013, 2020). Much of this literature has shed light on how financial conditions, leverage, and analyst coverage are

[5]We refer the reader to Fang and Yang (2022) for a detailed discussion about the relative merits and comparisons of each approach.

impacted by the degree of competitiveness in firms' corresponding product markets. Our study adds to this discussion by showing that a firm's survival risk profile might be impacted by preemptive product market investment strategies.

2 Theoretical Framework

The model of strategic firm investment we use is based on the canonical entry models used to study site selection decisions (Bresnahan and Reiss 1991). This framework allows us to analyze investment decisions (i.e., entry) at a granular investment-by-investment level, along with investment outcomes (i.e., *ex post* survival). Investment decisions are forward-looking and strategic, as firms base their decisions on the expected flow of future payoffs for each decision option, as well as expectations they have about their competitor's investment decision. To accommodate for these dimensions, our model is built on the dynamic oligopoly framework by Ericson and Pakes (1995).

2.1 Actions, Payoffs, and Equilibrium

In this model, there are two forward-looking and strategic firms,[6] i and j. Firms are forward looking with a discount factor of $\beta \in (0, 1)$, and seek to maximize their long-run discounted payoffs in an infinite horizon game. At the beginning of each time period t, the firms can choose whether or not to be active in a geographic product market. We let $a_{it} \in \{0, 1\}$ denote firm i's action at time t. The action space is $\mathcal{A} \equiv \{0, 1\}$. The payoff relevant state variables include the market size $z_t = (z_{it}, z_{jt})$ and market structure s_t. The active status of firm i is denoted with $s_{it} \in \{0, 1\}$. Then $s_t = (s_{it}, s_{jt}) \in S$, where $S = \{(0, 0), (0, 1), (1, 0), (1, 1)\}$ is the support for this market structure state. Both firms can observe z_t and s_t. Finally, as in typical games of incomplete information, we allow for a private idiosyncratic shock ε_{it}. Therefore, the payoff relevant states for firm i can be summarized by the tuple $(s_t, z_t, \varepsilon_{it})$.

[6] Models with two focal firms have been used in past literature about strategic incentives in dynamic games (Sweeting et al. 2020).

There is a sunk cost of entry, which we denote as EC_i. Entry costs may include expenses such as acquiring property to house the outlet. Finally, there is a scrap value from leaving a market, which we denote as SV_i. The scrap value may come from the amount recovered from liquidating an outlet (e.g., real estate value, equipment).

Next, we define the flow payoff functions. The revenue generated is denoted as $R_i(\cdot)$. Assuming that ε_{it} is additive and separable in the profit function, as well as i.i.d. With this notation, the payoffs can be written as

$$\Pi_i(a_{it}, a_{jt}, s_t, z_t, \varepsilon_t) \equiv R_i(a_{it}, a_{jt}, z_{it}) + C_i(a_{it}, s_{it}) + \varepsilon_{it}(a_{it}), \tag{1}$$

where we define the sunk costs as $C_i(\cdot) = (a_{it} - s_{it})[a_{it}EC_i + (1 - a_{it})SV_i]$ for each firm i.

Firms rely on stationary Markov strategies. As such, we omit the time subscript for simplicity. Let $\sigma = (\sigma_i(s, z, \varepsilon), \sigma_j(s, z, \varepsilon))$ be the strategy functions for the two firms. For each strategy profile σ, the conditional choice probabilities (CCPs) are defined as

$$P_i^\sigma(a_i = 1|s, z) \equiv \Pr(\sigma_i(s, z, \varepsilon_i) = 1|s, z) = \int I\{\sigma_i(s, z, \varepsilon_i) = 1\} f_i(\varepsilon_i) d\varepsilon_i. \tag{2}$$

By construction, $P_i^\sigma(a_i = 0|s, z) = 1 - P_i^\sigma(a_i = 1|s, z)$.

The payoff relevant states are summarized as $X = (s, z, \varepsilon)$. Given these payoff relevant states, the firms choose their strategies so as to solve the following recursive optimization problem:

$$V_i(X, \sigma) = \mathbb{E}[\Pi_i(X, \sigma(X)) + \beta\mathbb{E}(V_i(X', \sigma)|X, \sigma_i(X), \sigma_j(X)]. \tag{3}$$

Firms follow a Markov Perfect Equilibrium (MPE) such that the strategy profile satisfies the following condition for all i:

$$V_i(X, \sigma|\sigma_i^*, \sigma_j^*) \geq V_i(X, \sigma|\sigma_i, \sigma_j^*), \tag{4}$$

for all σ_i and all states X, where $V_i(\cdot)$ is a Bellman equation defined using the recursive problem above.[7] The strategy profile in equilibrium is defined such that no firm i has an incentive to deviate from the optimal strategy σ_i^*, in that no alternative strategy (σ_i) yields higher expected discounted profits than σ_i^* while its rivals use strategies σ_j^*.

2.2 Measuring Preemptive Motives

The definition and measure of preemptive motives used in this paper are based on Fang and Yang (2022), which derives a measure of preemptive motives for a dynamic discrete oligopoly game using a decomposition-based approach. Compared to other recent methods aimed at quantifying preemptive motives in the literature (Chicu 2013, Hünermund et al. 2014, Igami and Yang 2016, Zheng 2016), the Fang and Yang (2022) decomposition-based approach has the advantage of preserving the *direct competitive effect* while eliminating preemptive motives to the full extent; ultimately, keeping fixed the key *dynamic features* of the game between scenarios with and without deterrence motives. Compared to Igami and Yang (2016), the decomposition-based approach preserves the direct competitive effect; compared to Zheng (2016), our approach captures preemption to the fullest extent, and compared to the open-loop equilibrium in Hünermund et al. (2014), our approach permits firms to behave differently across the rivals' states and thereby removes "empty threats" present in an open-loop equilibrium. Furthermore, unlike open-loop equilibria, which could vary substantially based on the initial state of interest, our approach is invariant to initial states. In short, among all measures proposed in the literature, ours is the closet to being sub-game perfect; the only removal is preemption.

With this decomposition, we can ascertain the proportion of all entry motives that are driven by deterrence concerns in equilibrium.[8] By isolating the deterrence motives in equilibrium, we can then impose a counterfactual scenario that have firms ignoring these motives

[7]An attractive property of the MPE is that the number of equilibria is finite (Doraszelski and Escobar 2010).

[8]The technical details and theoretical justification this decomposition approach are described in Fang and Yang (2022).

when making equilibrium entry decisions. Doing so effectively eliminates the effect of deterrence *without* changing the underlying economic fundamentals. Being able to eliminate these deterrence motives will be important for establishing potential consequences of deterrence-motivated entry on *ex post* survival.

We now provide a conceptual overview of the decomposition-based approach by Fang and Yang (2022). In order to understand the intuition behind their decomposition, it is helpful to establish intuitively the main components that motivate entry. This components include capital investment, sales, and entry deterrence:

1. **Capital investment**: The capital investment component, which comes from the entry costs and scrap values that a firm pays upon entry or receives upon exit. A firm can optimize its timing of entry by anticipating changes in entry costs and scrap values in the future. If it expects that a sharp increase in entry costs in the future, it might choose to enter a market early in order to save costs. Similarly if it expects a high return from scrap values upon exit at a particular time in the future, it could also choose to enter today. This marginal benefit from entry is part of the future payoffs but is irrelevant to entry deterrence.

2. **Sales**: The single-agent-sales component represents a firm's net present value of streams of profits through sales in all future periods when its incumbency status has no impact on its rival's entry behavior. This component alone can motivate a firm to enter a market today, as long as the stream of profits in the future is large enough to cover the initial entry cost. However, this component does not account for the return on a firm's future profits through manipulating its action today in order to affect its rival's entry behavior in the future and thereby is not relevant to entry deterrence.

3. **Entry deterrence**: The entry-deterrence component captures the gain in a firm's net present value of future profits through the effect of its incumbency status on its rival's entry behaviors. This component represents a firm's preemptive motives. For example,

if a firm's being active in the market discourages its rival from entering the market in the next period, then by entering today, this firm can expect a higher probability of earning monopolistic profits in the future; as a result, this firm will enter the market aggressively today.

To "eliminate" the preemptive motives that lead to aggressive entry, we replace the rival's probability of entry at a firm's active state with a probability that corresponds to the firm's inactive state in the *future* portion of the marginal benefit from entry (in equilibrium). Through this replacement, a firm's incumbency status does not affect its rival's behavior in the future, and the deterrence motives are effectively eliminated. Based on these new equilibrium conditions, firms will choose an alternative set of optimal strategies, only that these new set of strategies are now purged of preemptive motives (i.e., deterrence motives are muted). Here, we reiterate that optimal strategies are employed by the firms, regardless of whether or not these strategies are preemptive.[9]

2.3 Measuring Survival

The concept of survival in our paper captures the extent to which an incumbent firm's strategy (i.e., exit market *ex post*) will change in the event that its rival becomes permanently more competitive. Such events are possible in our theoretical context as firms each receive private i.i.d. shocks ε_t. Thus, we interpret this concept as a "strategic stress test" as it helps us understand the confidence an outside observer might have about an investment strategy's *ex post* viability. This way, our measure of survival is centered around the *downside* strategic risks, as opposed to firm exit that is mechanically driven by prediction errors about future market size.

To illustrate this concept of survival, suppose an incumbent plays an aggressive strategy against its rival, and their strategies form an equilibrium. In the steady-state distribution,

[9] In Igami and Yang (2016), the scenario without preemptive motives is not in equilibrium, as they operationalize the scenario with no deterrence motives by making the incumbent compete with entirely non-strategic rivals. This effectively turns a dynamic game with multiple firms into a single-agent dynamic problem for the incumbent.

the incumbent would densely populate the markets with many outlets. However, if the rival receives a positive productivity shock that makes it permanently more competitive, the incumbent would need to change its equilibrium strategy. Consequently, the new strategies would lead to a new equilibrium for which the incumbent is unable to sustain a dense store network in the new steady-state distribution. Transitioning from a dense store network in the original equilibrium to a sparser network in the hypothetical new equilibrium implies that the incumbent would ultimately have to close many stores, leading to a large loss *ex post*.

To formalize this definition of survival, we consider two possible constructions. One version is based on firms' steady-state *density* of outlets, while the other version is based on firms' *values* at the steady-state.

2.3.1 Density-Based Survival Rate

Let $f^{\sigma}(s,z)$ denote the probability of state (s,z) in the steady-state distribution formed by a strategy profile σ, and μ^{σ}_{In} denote the proportion of the markets in which the incumbent firm (In) is active; that is, $\mu^{\sigma}_{In} \equiv \sum_{(s,z)} f^{\sigma}(s,z) I\{s_{In}=1\}$. The measure μ^{σ}_{In} can be seen as the expected proportion of markets in which the incumbent is active. Let $\mu^{MPE_b}_{In}$ denote the incumbent's expected number of outlets in the steady-state distribution resulting from the MPE before the rival becomes stronger, and $\mu^{MPE_a}_{In}$ denote the one after, then our measure of survival S^{MPE}_{In} is

$$S^{MPE}_{In} = \frac{\mu^{MPE_a}_{In}}{\mu^{MPE_b}_{In}}. \tag{5}$$

That is, the survival rate S^{MPE}_{In} measures what percentage of the incumbent's outlets survive after the change under the scenario with deterrence-motivated entry.

To examine the relationship between deterrence motives and survival, we need to obtain the survival rate of the incumbent for a counterfactual scenario where the incumbent plays a non-preemptive strategy both before and after the rival becomes stronger. The construction of that counterfactual has been described in Section 2.2. Let $\mu^{Ctf_b}_{In}$ denote the incumbent's expected number of outlets in the steady-state distribution in the counterfactual before the change and $\mu_{In}^{Ctf_a}$ after, the survival rate under the non-preemptive scenario is then:

$$S_{In}^{Ctf} = \frac{\mu_{In}^{Ctf_a}}{\mu_{In}^{Ctf_b}}. \tag{6}$$

Comparing S_{In}^{MPE} with S_{In}^{Ctf} gives us an idea whether there is a trade-off between aggression and survival in terms of firms' density of outlets, and if so, to what extent.

2.3.2 Value-Based Survival Rate

The value-based survival rate measures a different dimension of each firm's performance in the steady state. It compensates the potential weakness in the density-based measure; even though the incumbent can potentially maintain the density of outlets after change, the profitability for each outlet may be lower, and therefore, the overall profitability of the incumbent firm would be smaller. Lower profits lead to lower valuations of firms, which can put firms in precarious positions, especially when firms are highly leveraged or publicly traded companies. The value-based survival rate compares firms' capital valuation before and after the change. In other words, this measure represents how much firms' values have shrunk after their rivals become very competitive. This measure has practical importance, as a significant decrease in values could indicate a danger of bankruptcy *ex post*.

To measure each firm's capital valuation, we use the average of firms' continuation values at each state in the steady-state distribution. More specifically, the incumbent's valuation at the steady state is $\bar{V}_{In} \equiv \sum_{(s,z)} f^{\sigma}(s,z) V_{In}(s,z)$, where $V_{In}(s,z)$ is the continuation value of the incumbent at state (s,z). $V_{In}(s,z)$ is also known as the integrated value function in the literature (Aguirregabiria and Mira 2007) as this object integrates over firms' idiosyncratic shocks ϵ. Let $\bar{V}_{In}^{MPE_b}$ denote the incumbent's average valuation resulting from the MPE before the rival becomes stronger, and $\bar{V}_{In}^{MPE_a}$ denote the one after, then the value-based measure of survival VS_{In}^{MPE} is

$$VS_{In}^{MPE} = \frac{\bar{V}_{In}^{MPE_a}}{\bar{V}_{In}^{MPE_b}}. \tag{7}$$

To examine the relationship between preemptive motives and survival, we need to obtain the survival rate in the counterfactual scenario as well. Similarly defined, the value-based survival rate under the scenario where preemptive motives are absent is

$$VS_{In}^{Ctf} = \frac{\bar{V}_{In}^{Ctf_a}}{\bar{V}_{In}^{Ctf_b}}. \tag{8}$$

The difference between firms' survival rates under the preemptive scenario and those under the scenario with no deterrence motives will provide insights about the relationship between deterrence motives and *ex post* survival. In particular, if the difference is *negative*, then deterrence-motivated entry might be associated with higher *ex post* risks related to survival. We can construct the difference for the density-based survival measure (DDS) and value-based survival measure (DVS) as follows:

$$\begin{aligned} DDS &= S_{In}^{MPE} - S_{In}^{Ctf}, \\ DVS &= VS_{In}^{MPE} - VS_{In}^{Ctf}. \end{aligned} \tag{9}$$

3 Empirical Application

We now demonstrate how our theoretical framework can be implemented in order to assess the relationship between deterrence-motivated entry and survival. The empirical context pertaining to fast casual taco chain competition is described in Subsection 3.1, while the main results from this analysis is in Subsection 3.2.

3.1 Data

The product market under examination is the fast casual restaurant sector. For our empirical analysis, we focus on the two largest firms in Texas, Taco Cabana and Chipotle. Taco Cabana was founded in San Antonio, Texas in 1978, and mainly expanded in Texas. At its peak, it reached 162 outlets in 2014, and today still operates 160 stores in Texas. Chipotle is the other major firm in this sector, and entered Texas in late 2000.

Our data is derived from a multiple sources. The main data set that contains information regarding Chipotle's and Taco Cabana's outlets is part of the Mixed Beverage Tax Information Records kept by the Office of the Comptroller of Public Accounts in Texas. The raw data set includes detailed information on each establishment that holds a mixed beverage permit, including taxpayer's name and address, business location name and address, permit number, permit issue date, out of business date, gross receipts reporting date, liquor sales, beer sales, wine sales, and the total gross receipts which add up all sales from the previous three categories. Based on taxpayers' information and outlet names, we were able to identify with accuracy the outlets run by Chipotle and Taco Cabana. Each establishment's address is geocoded using a Google Maps API. Even though we have only revenue data for alcohol sales, the alcohol sales ratios between typical restaurants from these two restaurant chains closely reflect the actual profit ratios; this observation suggests that alcohol sales might be a good proxy for overall revenue for each location. Using company disclosures of net income and profits, Taco Cabana's annual profit was in the order of $280 million in the U.S. in 2017 and since it had about 173 restaurants at the time, per restaurant per month average sales were about $136,224. Our alcohol sales data average for Taco Cabana is about $3,849, roughly 3% of the monthly profit at each restaurant. For Chipotle, the annual profit at each restaurant was about $250,000 in 2014 in the U.S., which was about $20,833 per restaurant per month, and considering our data average of monthly alcohol sales at Chipotle was $721, we can see that the alcohol sales also account for about 3% of total profits at Taco Cabana.

One may interpret that Taco Cabana have larger restaurants restaurant (i.e., approximately 6.5 times larger than Chipotle outlets).

We complement this market structure and performance data with detailed market-time varying information about demographics (e.g., population, age brackets), income, infrastructure and traffic volume data from a number of sources, including the census, American Community Survey, and the Department of Transportation of Texas. A detailed account about each source is described in the Appendix.

With this information, we can form a panel that covers monthly mixed beverage sales for every outlet of Taco Cabana and Chipotle during the period of December 1993 to December 2015, demographic and income information for each census tract, and infrastructure and traffic information based on each outlet's location. Our sample includes 310 geographic markets in total (i.e., census tracts), spanning over 96 cities across 39 Texas counties. Census tracts are selected based on whether they eventually had an outlet open (at any point in time); this selection rule helps us avoid census tracts that are clearly not zoned for retail (as many tracts are zoned for residential and industrial use).

Table 1 summarizes the data we use to fit our model. Notice that given the granularity of our market-time information, we have over 80,000 observations to draw inferences from. Among all time-location markets, Chipotle is active in 15.1% of the markets, and Taco Cabana 35.8%. This pattern is consistent with Taco Cabana being the industry leader in fast casual dining in Texas. On average, Chipotle makes about $720 from selling alcoholic drinks every month in each market, while Taco Cabana makes about $3,850, almost 5.4 times as high as that of Chipotle's. This difference is in agreement with the casual observation that customers at Taco Cabana order more alcoholic drinks than those at Chipotle. Although we do not have the total monthly revenue for each restaurant, we assume in our analysis that sales from alcoholic beverages account for a constant proportion of a restaurant's monthly total revenue. Under this assumption, we write a restaurant's total revenue as $log(total\_revenue) = log(mixed\_beverage\_sales) + constant$. When summarizing our

Table 1: Summary Statistics for Calibration Data

Variable	Mean	Std. Dev.
Entry decisions		
Active status of Chipotle	0.151	0.358
Active status of Taco Cabana	0.358	0.479
Revenue		
Revenue for Chipotle	721.138	417.378
Revenue for Taco Cabana	3849.046	2619.112
Market Size Proxies		
Total population	5280.023	3008.664
Population density (persons per km^2)	1510.105	1096.258
Share of population (15-34)	0.341	0.131
Share of population (35-64)	0.362	0.0814
Share of population (65 and up)	0.0986	0.0615
Share of Hispanic population	0.252	0.191
Share of white population	0.563	0.139
Share of black population	0.105	0.122
Share of Asian population	0.0638	0.0875
Inflation adjusted income	59424.396	29912.966
Daily traffic for Chipotle	172.096	244.169
Daily traffic for Taco Cabana	231.594	374.489
In big urban area	0.826	0.379
Interstate highway	0.387	0.487
Primary or secondary road	0.819	0.385
N	82150	

structural model estimates in a subsequent section, we provide further justification for this assumption about constant proportions with respect to alcohol and total sales. As for the demand conditions, the daily traffic faced by Taco Cabana is higher than that by Chipotle. Taco Cabana has a weighted daily traffic of 232 persons/meter while Chipotle's is 172 persons/meter.[10] This difference in daily traffic explains partially the higher revenues of Taco Cabana.

For the geographic markets under consideration, the average total population is about

[10]The weighted daily traffic is constructed from dividing the daily traffic counts at a traffic monitoring station that each restaurant is closest to by the distance in meters between the station and that restaurant.

5,280 with a mean population density at 1,510 persons per square kilometers. Population from the 15-64 age cohort accounts for 70% of the total population, and in terms of race, white and Hispanic populations account for over 80% of the total population. The average income per household is about $59,000. Most markets are within the five largest urban areas, including Austin, Fort Worth, Dallas, Houston and San Antonio. Over one third of the markets are crossed by an interstate highway, and over 80% of the markets contain primary or secondary roads. This is not surprising considering that interstate highways and primary and secondary roads are the main locations for the outlets of these two restaurant chains. The Appendix offers additional patterns in the data that describe the dynamics in this industry.

3.2 Main Findings

The dynamic oligopoly model for investment is estimated using the two-step forward simulation approach by Bajari et al. (2007).[11] With the fitted model, we traverse through the parameter space to uncover conditions for which *ex ante* preemptive motives pose a risk to *ex post* survival. In particular, we illustrate (with respect to the parameter space) the difference in density-based survival rates (i.e. DDS) and value-based survival rates (i.e., DVS) for both firms. This comparative static analysis largely focuses on two main categories of model primitives:

1. **Competition conditions**, including strategic interaction parameters (i.e. Taco Cabana's competitive effect on Chipotle and Chipotle's on Taco Cabana).

2. **Cost conditions**, including entry costs and scrap values.

To avoid confounding factors in our simulation analysis, we use the average market in

[11]Technical details about the steps in our estimation procedure, along with model estimates, are provided in the Appendix. An attractive feature of this approach, as compared with other two-step methods (Aguirregabiria and Mira 2007, Pakes et al. 2007), is that it easily accommodates for continuous state variables. Being able to use continuous state variables allows us to avoid discretizing sales data. In general, dynamic models are potentially sensitive to assumptions regarding the coarseness of the discretized state space (Lanz et al. 2022).

Texas as a benchmark and assume that the market size has reached steady state. Therefore, only the market structure in terms of which firm is active changes over time. This simplification reduces the computational burden in the first round of simulation analysis and helps us draw economic intuition as to why certain phenomena arise. These simulations rely on a calibrated model, whereby the estimated structural primitives are described in the Appendix. In the simulations, the inferred structural primitives related to profits are shown in Table A5 in the Appendix, while the primitives related to entry and exit costs are shown in Table A3 in the Appendix.[12]

With the estimated model, our analysis requires us to explicitly solve the dynamic model. To solve the model, we employ the computational method developed by Borkovsky et al. (2010), which leverages homotopy methods. Homotopy methods essentially search for equilibria by following the equilibrium paths in the structural parameter space as we vary the structural parameters. A homotopy method is a sophisticated method for obtaining an exhaustive set of complicated solutions to dynamic games, especially when multiple equilibria exist.[13] It proceeds by first solving a simpler version of the original (i.e., complicated) problem, and then gradually transforms the simplified problem into successively more complex problems. By making iterative and small adjustments to the initial solution to the simple problem, this algorithm solves the original complicated problem. These iterations form a path of solutions, known as the homotopy path. We refer the reader to the Appendix for more of the technical details of this algorithm. Compared to alternative approximation-based computational methods, the homotopy method is likely to capture a more comprehensive set of multiple equilibria. Through a comprehensive search, we are able to find one equilibrium, which may provide some assurance that the equilibrium generating the data is the same type

[12]Note that the real estate rental costs may vary across market size. However, that is a per-period fixed cost and is not accounted for in the initial costs of entry or liquidation cost after exit.

[13]An alternative approach would be to use approximation dynamic programming methods or reinforcement learning. Examples of how these approaches can be used include Igami and Yang (2016), Pakes et al. (1994) and Pakes and McGuire (2001). As our focus is to compare various equilibria, it is important for us to obtain a complete set of solutions. Approximation methods might not allow researchers to obtain as comprehensive of a set of multiple equilibiria that homotopy methods are able to.

of equilibrium that is used to solve the counterfactuals.

3.2.1 Competition Conditions

In the four graphs that follow, we highlight the simulation results by showing the difference in density-based survival rates (DDS) and that in value-based survival rates (DVS) for both Taco Cabana and Chipotle. Figures 1 and 2 illustrate the density-based results for Taco Cabana and Chipotle, respectively, and Figures 3 and 4 demonstrate those for value-based measures. These figures show results for the parameter space formed by the competitive parameters, while holding other model primitives constant.

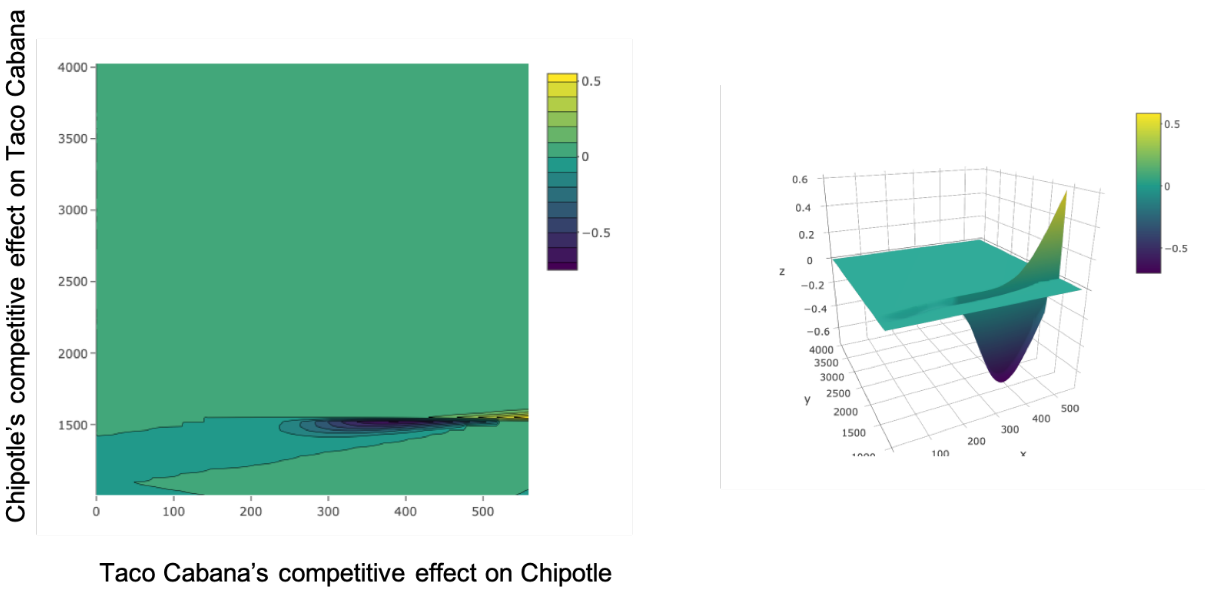

Figure 1: Profitability Space: Difference in Density-Based Survival Rates for Taco Cabana

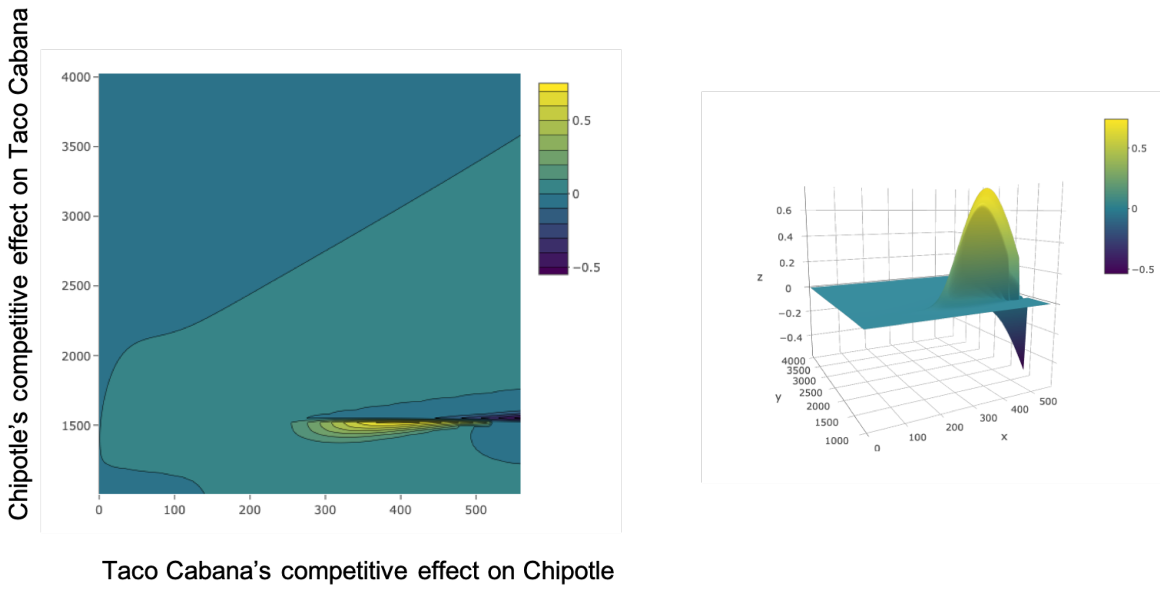

Figure 2: Profitability Space: Difference in Density-Based Survival Rates for Chipotle

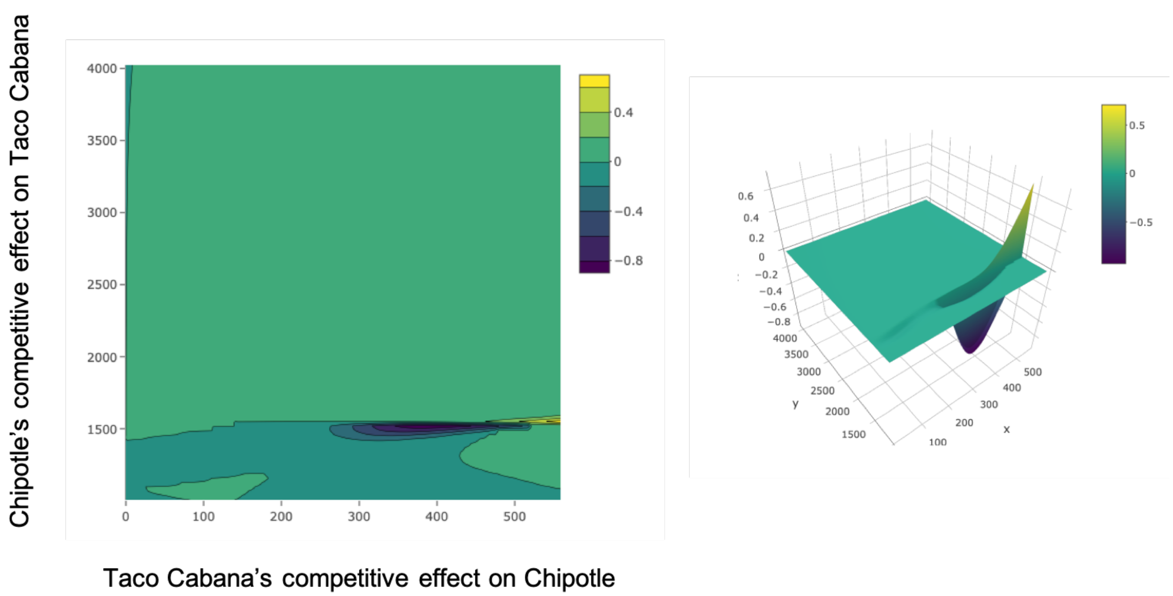

Figure 3: Profitability Space: Difference in Value-Based Survival Rates for Taco Cabana

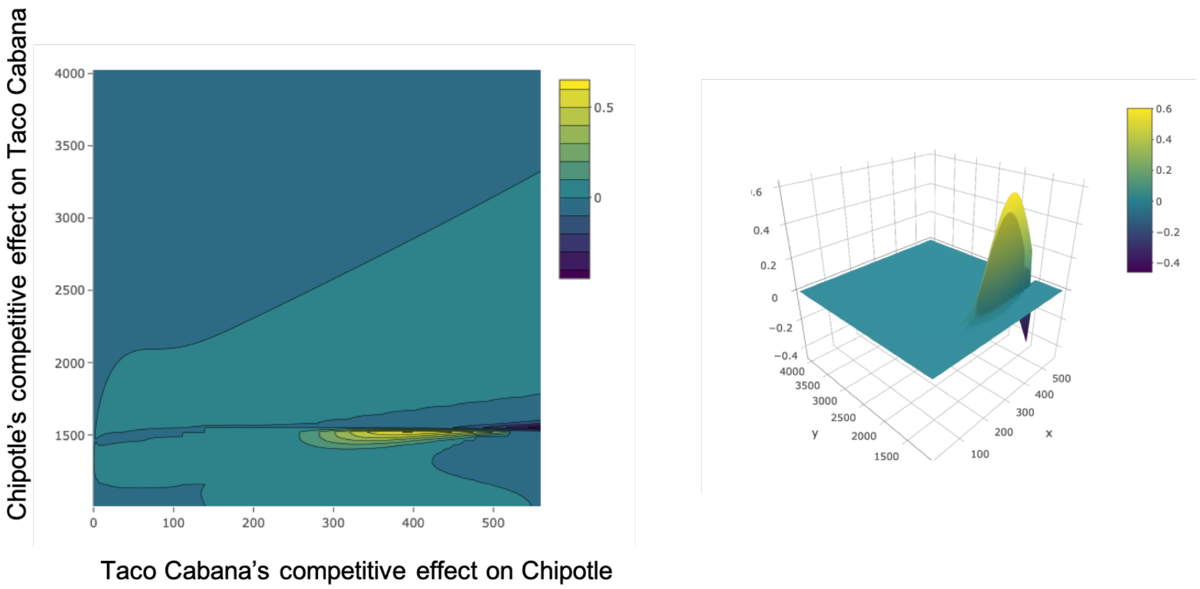

Figure 4: Profitability Space: Difference in Value-Based Survival Rates for Chipotle

As shown in Figure 1, the difference in density-based survival rates between MPE and the non-preemptive scenario for Taco Cabana is negative in certain regions of the parameter space and positive in others. This indicates that the relationship between aggression and survival is somewhat nuanced.

First, for a large region of the parameter space, the bright green to yellow area, deterrence-motivated entry appears to positively impact *ex post* survival of the incumbent Taco Cabana. In particular, for the small narrow band where Taco Cabana's competitive effect on Chipotle is about $430 and above and where Chipotle's competitive effect on Taco Cabana ranges from about $1,600 to $1,700, this difference in survival rate between preemptive and non-preemptive scenario is very pronounced, with the survival rate under the preemptive scenario bigger than the non-preemptive one by almost 0.6 or 60%. For the region outside of this narrow band, where aggression *improves* survival, the difference in density-based survival rates is small, suggesting that firms' aggressive and non-aggressive strategies result in a similar survival rate.

Second, for a relatively narrow band up to $1,600 on the spectrum of Chipotle's competitive effect on Taco Cabana and to $520 on the spectrum of Taco Cabana's competitive effect on Chipotle, the difference in density-based survival rates between MPE and the non-aggressive scenario is negative, as indicated by the turquoise and darker blue colour on the graph. In this region, aggression appears to harm the survival of Taco Cabana. In particular, for a very narrow valley in the area between $1,400 to $1,600 on the scale of Chipotle's competitive effect on Taco Cabana and $240 to $520 on the scale of Taco Cabana's competitive effect on Chipotle, the difference is very pronounced, with the lowest point going below -0.7 or -70%. This big difference in survival rate implies that when the competitive parameters lie in this region, aggression severely *harms* survival.

As a brief digression, we note that the figures also illustrate that as Chipotle's competitive effect on Taco Cabana increases, the relationship between deterrence-motivated entry and survival becomes non-monotonic as critical regions of the parameters exist in which the relationship between deterrence-motivated entry and survival can flip sign.

To complement the results for Taco Cabana's survival rates, we also show Chipotle's survival rates by the same measure in Figure 2. As can be seen, the graph is almost the flip image of Taco Cabana's survival rate graph Figure 1. For the very narrow band where the difference in survival rate between scenario with deterrence motivates and scenario without deterrence motives is very pronounced, the DDS is almost the exact opposite between the two graphs, meaning that the region where deterrence-motivated entry jeopardizes survival for Taco Cabana also coincides with regions for which deterrence-motivated entry can actually improves Chipotle's survival *ex post*.

Nonetheless, there exist areas in the parameter space where deterrence-motivated entry harms the survival of both firms; for example, the area very close to the left bottom corner of the graph where Chipotle's competitive effect on Taco Cabana ranges from $1,006.29 to $1,250 and Taco Cabana's on Chipotle ranges from $0 to $130. This area indicates that if Chipotle's competitive effect on Taco Cabana increases whereas Taco Cabana's on Chipotle decreases, both firms would be better off without playing an deterrence-motivated strategy.

Areas in the parameter space where deterrence-motivated entry benefits the survival of both firms also exist; for example, the space enclosed by Chipotle's competitive effect on Taco Cabana between $2,000 and $2,500 and Taco Cabana's on Chipotle between $300 and $500. This area suggests that if both firms' competitive effects on each other increase, deterrence-motivated entry can be associated with increased survival rates. Furthermore, this region also implies that without deterrence motives, both firms will build a sparser store network.

Figures 3 and 4 illustrate the results for value-based survival measures (DVS) for Taco Cabana and Chipotle respectively. As can be seen, the patterns are qualitatively very similar to those shown in density-based measures.

A general pattern from these graphs, in particular Figure 1, is that in the region up to $1,600 for the parameter of Chipotle's competitive effect on Taco Cabana and up to $450 for Taco Cabana's competitive effect on Chipotle, Taco Cabana's deterrence-motivated entry becomes increasingly harmful to *ex post* survival as Chipotle becomes more competitive. In other words, Taco Cabana's survival rate under the deterrence-motivated scenario is increasingly smaller than that under the scenario with no deterrence motives as Chipotle's competitive effect on Taco Cabana increases. This result is intuitive given that as Chipotle becomes more competitive, Taco Cabana's ability to deter entry and dominate the market decreases.

Also within this region, we observe that Taco Cabana's negative relationship between deterrence and survival worsens further monotonically as Taco Cabana's competitive effect on Chipotle increases. This result is counter-intuitive at first glance. If Taco Cabana exerts more competitive pressure on Chipotle, Taco Cabana should have a higher ability to preempt the entry of Chipotle, and thereby resulting in a higher survival rate under the aggressive scenario than that under the non-aggressive scenario, contrary to what Figure 1 shows.

Upon closer examination, however, this result above can indeed be rationalized, which we demonstrate by way of an example. Let us fix Chipotle's competitive effect on Taco Cabana at just below $1,500. Figures 1 and 2 show that aggression hurts survival for Taco Cabana but helps Chipotle survive as Taco Cabana's competitive effect on Chipotle increases.

This implies that Chipotle in fact is playing an increasingly aggressive strategy along this parameter dimension. As Taco Cabana's competitive effect on Chipotle increases up to \$450–\$500, Chipotle's incentive to preempt the entry of Taco Cabana's stores in certain markets increases because the coexistence of both chains' stores really hurts Chipotle. To reduce the possibility of coexisting with Taco Cabana and to have more markets where Chipotle is the only active chain, Chipotle would employ an deterrence-motivated entry strategy. In addition, since its competitive effect on Taco Cabana is relatively large at \$1,500, its aggressive strategy is effective enough to either deter Taco Cabana's entry or drive out Taco Cabana's stores in certain markets.

However, the beneficial effect of Chipotle's deterrence-motivated strategy does not persist once Taco Cabana's competitive effect on it goes beyond around \$530. After this point, no matter the level of Chipotle's competitive effect on Taco Cabana, deterrence-motivated entry always help Taco Cabana survive. The yellow and bright green colour on Figure 1 in the region beyond \$530 demonstrate this result: when Taco Cabana's competitive effect on Chipotle is too strong, preemptive strategy from Chipotle is going to hurt Chipotle's profits so much that the sacrifice involved in a preemptive strategy outweighs the gain. As shown in Figure 2, in this region beyond \$530, aggression hurts Chipotle's survival.

Another general pattern shown in Figure 1 is that in the region beyond \$530 on the horizontal-axis and \$1,600 on the vertical-axis, the extent to which deterrence-motivated entry increases Taco Cabana's survival rate grows monotonically with Taco Cabana's competitive effect on Chipotle. This pattern seems consistent with the notion that Taco Cabana's large competitive effect would make a deterrence strategy effective because its presence hurts Chipotle's profit. By entering aggressively, Taco Cabana could either preempt the entry of Chipotle or drive out Chipotle's existing stores in some markets. In this region, the extent that aggressive entry can help Taco Cabana survive also diminishes as Chipotle's competitive effect on Taco Cabana increases. If Chipotle's presence has a significant negative impact on Taco Cabana, then the sacrifice involved in a deterrence strategy for Taco Cabana is too large and may not be worth the benefit of being the monopoly. Therefore, the higher Chipotle's competitive effect on Taco Cabana renders Taco Cabana's deterrence strategy too costly.

We also note that Taco Cabana exhibits strong preemptive behaviors only for a narrow band in the parameter dimension of Chipotle's competitive effect on Taco Cabana. In the region beyond \$530 on the horizontal-axis in Figure 1, Taco Cabana's aggressive behaviors are only pronounced in the range of \$1,500 and \$1,600 on the vertical-axis. This narrow yellow area can be seen as the "sweet spot" where Taco Cabana's deterrence motives are the strongest because Chipotle's presence now hurts Taco Cabana's profit more than before, and Taco Cabana is becoming more proactive in driving out Chipotle. In addition, at a competitive effect on Chipotle beyond \$530, preemptive strategy is effective for Taco Cabana. For any parameter value below \$1,500 in the region beyond \$530 on horizontal-axis, Taco Cabana can be less proactive because although Chipotle's presence hurts profit, it does not hurt too much.

In summary, deterrence-motivated entry does not appear to elevate survival risk provided that the following three competitive conditions hold:

1. A rival's presence has to hurt a firm's profit large enough such that deterrence-motivated entry creates a payoff for the firm.

2. The damage of the rival's presence on the firm's profit should not be so extensive that it hurts the firm too much to deter.

3. A firm has to be competitive enough and its presence has to hurt its rival's profit enough such that deterrence-motivated strategies are effective.

These three main factors determine that in the broader parameter space of firms' competitive effects on each other, the preemptive effect is not monotonic overall, but instead could be monotonic in certain regions. Also since all three factors have to be met at the same time, the preemptive regions where there is a favorable relationship between aggression and survival will be relatively narrow in the parameter space.

3.2.2 Cost Conditions

Next, we now explore the relationship between deterrence-motivated entry and survival in the sunk cost space. Here, we hold the incumbent Taco Cabana's sunk costs as well as its profitability parameters constant, and only vary the entrant's sunk costs, including both the entry cost and scrap value. This treatment is consistent with the overall theme of examining what happens to the incumbent's survival rate when the rival becomes stronger. Figures 5 and 6 show the density-based results for Taco Cabana and Chipotle respectively, and Figures 7 and 8 display those for value-based measures.

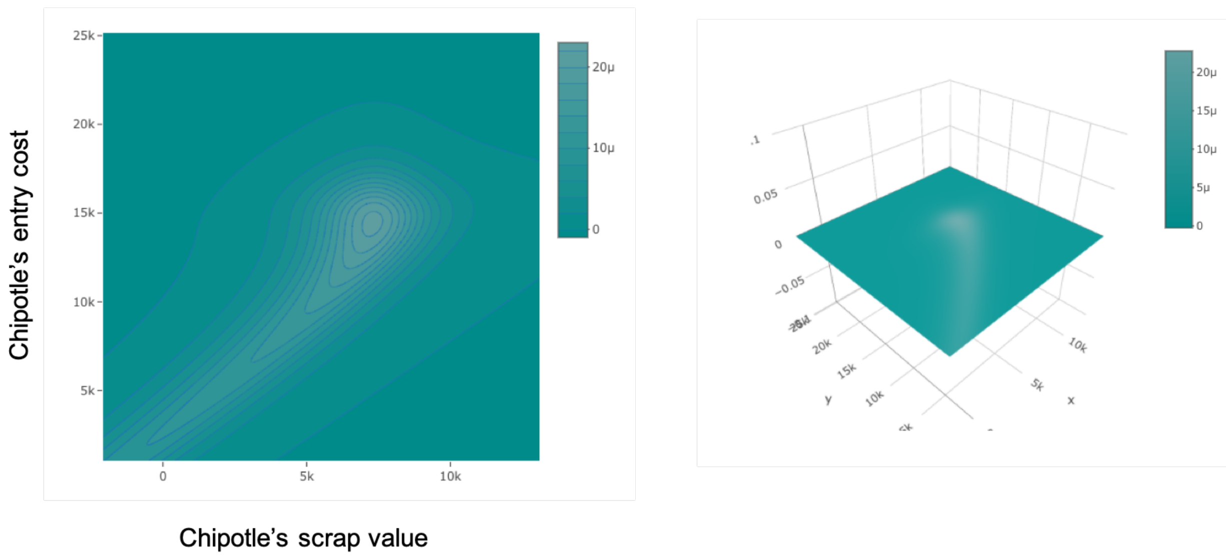

Figure 5: Sunk Cost Space: Difference in Density-Based Survival Rates for Taco Cabana

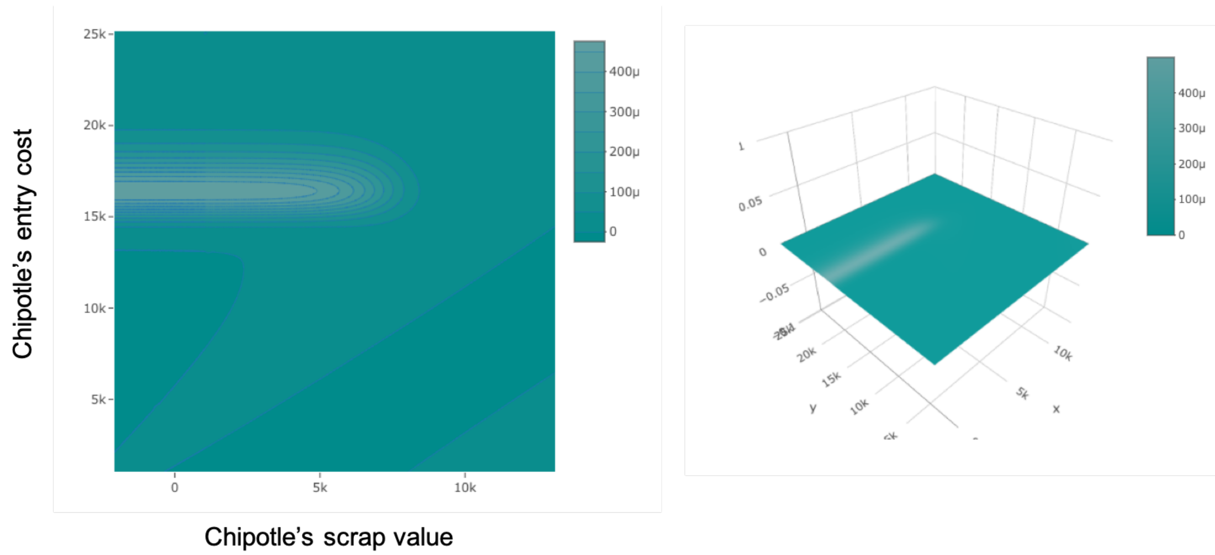

Figure 6: Sunk Cost Space: Difference in Density-Based Survival Rates for Chipotle

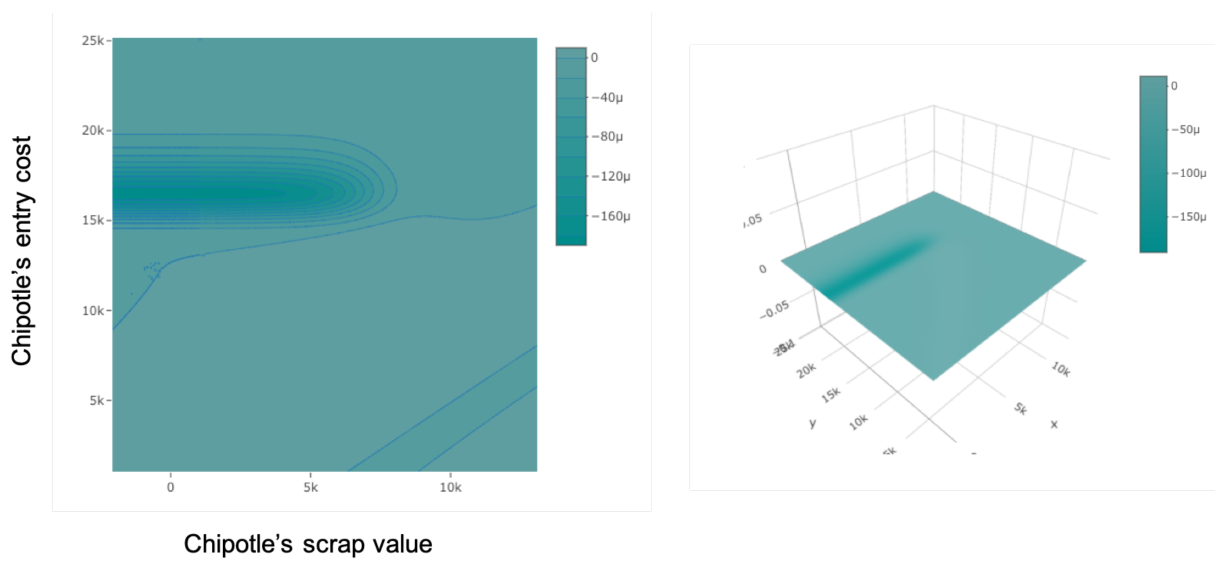

Figure 7: Sunk Cost Space: Difference in Value-Based Survival Rates for Taco Cabana

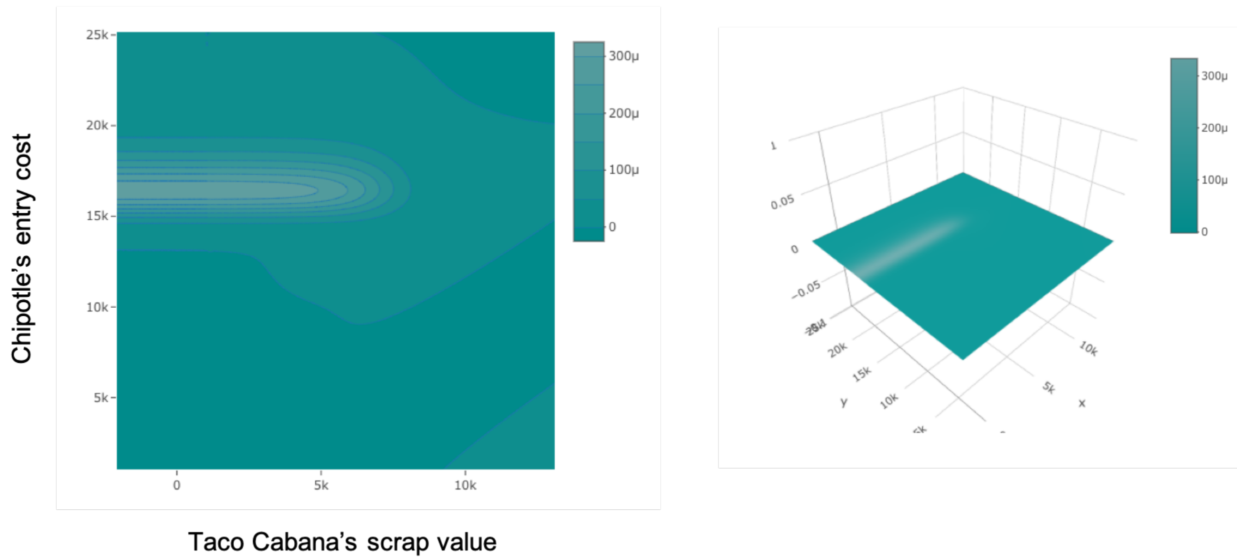

Figure 8: Sunk Cost Space: Difference in Value-Based Survival Rates for Chipotle

The results from both the density-based and value-based measures show that the dimension of a rival's sunk costs does not affect firms' survival rate difference between the preemptive and non-preemptive scenarios. In other words, firms' survival rates look very much the same with and without deterrence motives. As shown in all figures, the difference in survival rates is in the order of 0 to 10^{-4}. These results run contrary to the conventional wisdom that entry costs and scrap values are key factors for aggressive entry (Judd 1985, Cabral and Ross 2008).[14]

Taken together, our simulation analysis reveals that sunk costs do not appear to impact the *ex post* risks on survival associated with deterrence-motivated entry, unlike the underlying competitive conditions between firms.

4 Conclusion

Our research provides analytical and empirical insights about the relationship between deterrence-motivated investment and *ex post* survival. In particular, this analysis helps cov-

[14]We provide a more detailed discussion in the Appendix to reconcile our findings with the past theoretical insights about the role of sunk costs in deterrence.

ers the conditions (i.e., extent of business stealing, sunk costs) to which deterrence-motivated entry can harm *ex post* establishment survival. Furthermore, a data-driven simulation analysis uncovers non-monotonic patterns between the incumbent's (i.e., Taco Cabana) lower survival rates from deterrence-motivated entry, and the potential entrant's (i.e., Chipotle) competitive effect on the aggressor.

As a potential caveat, our empirical study abstracts away from other potential risks associated with deterrence-motivated entry. For example, aggressive entry may introduce the following risks as well, above and beyond a failure to deter entry. First, channel conflicts between franchisors and franchisees are more likely to occur (Blair et al. 2005), as strategies aimed to saturate local (or nearby) markets will likely lead to own-brand cannibalization (Jia 2008, Kalnins 2004, Pancras et al. 2012). Second, deterrence-motivated entry may preclude a firm from observational learning about the market's potential from past entry decisions if there is uncertainty about market size (Shen 2014, Yang 2020) or rival behavior/types (Aguirregabiria and Magesan 2020, Aguirregabiria and Jeon 2020, Doraszelski et al. 2018, Fershtman and Pakes 2012, Goldfarb and Xiao 2011). Finally, deterrence-motivated entry might lead to greater antitrust scrutiny if such strategies lead to monopolistic markets (Schmalensee 1978). Taken together, we believe future work could investigate how the benefits from deterrence-motivated entry balance against these other risks.

Moreover, our theoretical framework does not take into account the financing options firms have when opening new establishments. Theoretically, it has been shown that debt can be a strategic instrument to deter entry (Dixit and Kyle 1985, Firoozi and Lien 2010, Jain et al. 2003, Martin 2003, McAndrews and Nakamura 1992). While leverage information at the firm-level is widely available, the degree of leverage associated with each location is often kept confidential by the company, especially if the financing conditions likely vary from market to market. Nevertheless, we believe that such leverage information with this level of geographic granularity would be valuable for future research, as new intertemporal trade-offs could conceivably emerge. In particular, the availability of financing could potentially reduce the sunk costs of entry (i.e., short-run benefit), while at the same time, put added pressure on the firm to generate high margins in subsequent time periods (i.e., future benefit), in addition to the possibility of eventually requiring debt refinancing (Danis et al. 2014). Deterrence efforts that fail *ex post* would thus exacerbate the long-run risks associated with aggressive investment.

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Appendix

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A Data Sources for Market Size Proxies

For demographics and income, our data come mostly from the 1990-2010 decennial censuses. To control for the census geographic boundary definition changes during the three decennial census periods, we use GeoLytics's harmonized census data-set, the Neighborhood Change Database (NCDB) Tract Data from 1970-2010. This database adjusts earlier censuses to 2010 census geography, making feasible the inter-temporal comparison of demographic changes in a given area. The smallest geography in this database is the census tract, which we choose as our market definition. For the intercensal and post-censal periods, we use US Census Bureau's intercensal estimates and American Community Survey. The intercensal estimates and some American Community Survey data are available only at the county level; we distribute them to the census tract level based on historical trends.

For information on local infrastructure and traffic volume related to each outlet, we collect traffic volume data and Texas road network GIS shape-files from the Department of Transportation of Texas. For chain restaurants like Taco Cabana and Chipotle, traffic volumes are often one of the most direct demand indicators. The traffic volume data includes annual average daily traveler counts for about 31,400 traffic monitoring stations in Texas. It covers the years of 1999 to 2014. We extrapolated the traffic data for years outside of this range in our data-set. The Texas road network file is used to detect if an outlet is close to an interstate highway or primary and secondary roads in order to account for potential unobserved demand or cost factors.

B Supplementary Descriptive Analysis

We now highlight some of the raw entry patterns for the empirical application. From Table A1, geographic markets appear to be competitive as the two firms often avoid co-locating in the same markets, perhaps due to business stealing concerns. There is also some heterogeneity in each firm's sensitivity to its rival's presence, as Taco Cabana exhibits more sensitivity to competition relative to Chipotle's sensitivity. Our final observation is that Taco Cabana appears to have a greater presence across the markets.

Table A1: Tabulation of Market Configurations Across All Market-Time Observations

	Taco Cabana not active	Taco Cabana active
Chipotle not active	42,568	27,211
Chipotle active	10,194	2,177

Next, we present some descriptive patterns that motivate our assumption of no permanent market-specific heterogeneity. A sign that market heterogeneity is biasing the key model estimates about strategic interactions is if they become dampened (i.e., appearance of softer competition) or complementary (i.e., counterintuitive positive effects from competition), as discussed extensively in Igami and Yang (2016). To confirm that these symptoms of bias are not present, we consider "model-free" simple linear probability regressions of how rival presence affects the focal firm's entry. Across all of the specifications, we confirm that rival presence does indeed have a negative effect on entry. Most importantly, we never see the signs flipped (or dampened) when market fixed effects are introduced.

C Estimation and Identification

To estimate our model, we will follow the two-step approach developed by Bajari et al. (2007). The first stage of estimation is used to approximate the policy function, while the second stage of estimation is used to recover the underlying sunk cost parameters, $\gamma = (EC_i, EC_j, SV_i, SV_j)$. As in Bajari et al. (2007), we assume that the data observed are generated by a single MPE strategy profile, which then allows us to pool markets during estimation.

The model of entry we estimate is fairly standard, so we will provide a heuristic description about identification of our model. As per the discussion in Bajari et al. (2009),

Table A2: Linear Probability Regression with and without Market Fixed Effects

	Chipotle		Taco Cabana	
Rival presence	-0.118***	-0.0726**	-0.272***	-0.0713**
	(0.0225)	(0.0231)	(0.0434)	(0.0261)
Total population	-0.0000465	-0.00000390	-0.0000296	-0.00000716
	(0.0000311)	(0.00000623)	(0.0000468)	(0.00000891)
Population density	1.409	-1.663	-1.231	1.053
	(10.77)	(4.260)	(17.74)	(5.064)
Population (15-34)	0.0000838*	0.00000712	-0.0000189	0.0000113
	(0.0000368)	(0.00000850)	(0.0000472)	(0.00000917)
Population (35-64)	0.0000627	0.00000647	0.0000143	0.000000609
	(0.0000506)	(0.00000895)	(0.0000698)	(0.0000118)
Population (65 and up)	0.0000229	-0.0000150	-0.0000704	0.0000172
	(0.0000326)	(0.0000115)	(0.0000583)	(0.0000109)
Hispanic population	-0.00000205	-0.000000543	0.0000243	-0.000000524
	(0.00000539)	(0.00000201)	(0.0000130)	(0.00000275)
White population	-0.00000823	0.00000245	0.0000143	0.00000154
	(0.00000670)	(0.00000161)	(0.0000150)	(0.00000210)
Black population	-0.00000657	0.00000107	0.0000292	0.000000979
	(0.0000115)	(0.00000253)	(0.0000256)	(0.00000391)
Asian population	-0.00000831	-0.00000340	0.0000111	0.00000452
	(0.0000133)	(0.00000357)	(0.0000209)	(0.00000447)
Inflation adjusted income	0.00000154***	-8.02e-08	-0.00000176*	5.49e-08
	(0.000000425)	(0.000000129)	(0.000000761)	(0.000000166)
Time trend	0.00150***	0.00148***	0.00155***	0.00103***
	(0.000163)	(0.000183)	(0.000181)	(0.000163)
Daily traffic	0.00140***	0.00128**	0.000763*	0.00126***
	(0.000398)	(0.000469)	(0.000299)	(0.000327)
Constant	-0.124***	-0.0512**	0.308***	0.123***
	(0.0360)	(0.0182)	(0.0800)	(0.0322)
Observations	82150	82150	82150	82150
R^2	0.2234	0.2437	0.1254	0.1322
Market fixed effects	No	Yes	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

non-parametric identification of a dynamic game requires firm-specific states that affect the payoffs $\Pi_i(a_{it}, a_{jt}, s_t, z_t, \varepsilon_t)$. By construction, our model has such states. First, s_{it} has a direct impact on i via i's entry cost and scrap value, while s_{it} has no direct impact on rival j. Furthermore, we also allow for potential exogenous revenue factors, z_{it}, that uniquely affect i.

We now proceed by discussing each of the steps involved in the Bajari et al. (2007) estimation approach. The first step involves approximation of the CCPs using raw data patterns, and with the approximated policy functions, the second step uses forward simulations and minimum distance estimation to infer the model parameters.

C.1 Policy Function Approximation

To approximate the policy function σ_i, we employ a flexible probit model. That is, we use the following reduced form specification

$$\hat{\sigma}_i = \hat{P}_i^{\sigma} = \Phi(g(s, z)), \tag{10}$$

where $\Phi(\cdot)$ is the c.d.f. for a Normal distribution, and $g(s, z)$ is a flexible link function of the market structure states s and exogenous market states z.

Before pursuing the second stage of estimation, we also need to establish the relationship between observed sales, and the payoff relevant states (s, z). We use the following regression to map revenue (in markets that i is active in) onto the payoff relevant states associated with those markets.

$$R_i = \theta_{i1} a_j + \theta_{i2} z_i + \nu_i, \tag{11}$$

where ν_i is an i.i.d. demand shock, which represents unobserved state variables related to demand. We allow for potential business stealing effects to operate through θ_{i1}. With the revenue regression estimated, we can then obtain a predicted value for revenue, $\hat{R}_i$, for any given state z and rival j's entry decision a_j.

The fact that we have revenue information in dollar amount also allows us to estimate the variance of ε, which in turn translates the estimated entry costs and scrap values into dollar amount. A detailed discussion on this normalization approach is shown later in the Appendix.

C.2 Forward Simulation and Minimum Distance Estimation

With the approximated policy function and fitted revenue function in hand, we then proceed with the second step of estimation. For any given initial state (X_1), we can then forward simulate the following for firm i in market m:

$$\bar{V}_{i,m}(X_1;\sigma,\gamma) = \mathbb{E}\left[\sum_{\tau=1}^{\infty}\beta^{\tau-1}\Pi_{i,m}(\sigma(X_\tau)),X_\tau;\gamma)\,\middle|\,X_1,\sigma\right] \tag{12}$$

$$\simeq \frac{1}{\bar{K}}\sum_{k=1}^{\bar{K}}\sum_{\tau=1}^{T}\beta^{\tau-1}\Pi_{i,m}(\sigma(X_\tau^k)),X_\tau^k;\gamma). \tag{13}$$

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.

With this construction of forward simulated actions and payoffs, we can then consider perturbations of the policy function to generate B alternative policies. We generate these alternative policies by introducing random shocks to the parameters that govern the first-stage policy function approximations. With each alternative policy, we can obtain the forward simulated profit stream using the previous two steps. We let b index the individual inequalities, with each inequality consisting of an initial market structure and state $X_1^b = (s_1^b, z_1^b, \varepsilon_1^b)$, an index for the deviating firm i, and an alternative policy $\tilde{\sigma}_i$ for firm i. The difference in valuations for firm i in market m using inequality b is denoted by

$$h_{i,b,m}(\hat{\sigma},\gamma) = \bar{V}_{i,m}(X_1^b;\hat{\sigma},\gamma) - \bar{V}_{i,m}(X_1^b;\tilde{\sigma}_i,\hat{\sigma}_{-i},\gamma), \tag{14}$$

This difference should be positive in equilibrium, since off-equilibrium values has to be lower than discounted profits under equilibrium play. Therefore, this criterion listed below identifies a $\hat{\gamma}$ to minimize the violations of the equilibrium requirement:

$$Q(\gamma) = \frac{1}{B} \sum_m \sum_i \sum_b (\min\{h_{i,b,m}(\hat{\sigma}, \gamma), 0\})^2. \tag{15}$$

C.3 Interpreting Entry Costs and Scrap Values

Since we have revenue information in dollar amount also allows us to estimate the variance of ε_i, i.e. σ_{ε_i}, which in turn translates the estimated entry costs and scrap values into dollar amount. To see this, we can write the equilibrium condition of this game as[15]

$$P_i^{\sigma}(a_i = 1|s, z) = \frac{exp\left(\frac{\tilde{v}_i(s,z)}{\sigma_{\varepsilon_i}}\right)}{1 + exp\left(\frac{\tilde{v}_i(s,z)}{\sigma_{\varepsilon_i}}\right)} \tag{16}$$

where $\tilde{v}_i(s, z)$ is the difference in firm i's values between taking the decision to be active today and to be inactive. More specifically, $\tilde{v}_i(s, z)$ consists of several components:

$$\tilde{v}_i(s, z) = \tilde{\eta}_{i\pi} + \tilde{\eta}_{iec} + \tilde{\eta}_{isv} + \tilde{\eta}_{ie} \tag{17}$$

where $\tilde{\eta}_{i\pi}$ is the difference in the net present value of profits between the decision to be active in the market and the decision to be inactive. Similarly defined, $\tilde{\eta}_{iec}$ is the difference in the net present value of entry costs EC_i, $\tilde{\eta}_{isv}$ is the difference in the net present value of scrap values SV_i, and $\tilde{\eta}_{ie}$ is the difference in the net present value of the idiosyncratic shocks ε_i conditional on firm i's actions.

Given the estimated conditional choice probabilities (CCPs) P_i in the first-stage estimation, all four components of $\tilde{v}_i(s, z)$ can be expressed as functions of the CCPs, and key structural parameters of the model. In particular, the equilibrium condition 16 can be

[15] We assume that ε_i follows an extreme value type I distribution.

reorganized into

$$P_i^\sigma(a_i = 1|s, z) = \frac{exp\left(\frac{\tilde{\eta}_{i\pi}}{\sigma_{\varepsilon_i}} + \frac{EC_i\hat{\hat{\eta}}_{iec}}{\sigma_{\varepsilon_i}} + \frac{SV_i\hat{\hat{\eta}}_{isv}}{\sigma_{\varepsilon_i}} + \frac{\sigma_{\varepsilon_i}\hat{\hat{\eta}}_{ie}}{\sigma_{\varepsilon_i}}\right)}{1 + exp\left(\frac{\tilde{\eta}_{i\pi}}{\sigma_{\varepsilon_i}} + \frac{EC_i\hat{\hat{\eta}}_{iec}}{\sigma_{\varepsilon_i}} + \frac{SV_i\hat{\hat{\eta}}_{isv}}{\sigma_{\varepsilon_i}} + \frac{\sigma_{\varepsilon_i}\hat{\hat{\eta}}_{ie}}{\sigma_{\varepsilon_i}}\right)}$$
$$= \frac{exp\left(\theta_{i\pi}\tilde{\eta}_{i\pi} + \theta_{iec}\hat{\hat{\eta}}_{iec} + \theta_{isv}\hat{\hat{\eta}}_{isv} + \hat{\hat{\eta}}_{ie}\right)}{1 + \exp\left(\theta_{i\pi}\tilde{\eta}_{i\pi} + \theta_{iec}\hat{\hat{\eta}}_{iec} + \theta_{isv}\hat{\hat{\eta}}_{isv} + \hat{\hat{\eta}}_{ie}\right)} \tag{18}$$

where $\tilde{\eta}_{iec} = EC_i\hat{\hat{\eta}}_{iec}$, $\tilde{\eta}_{isv} = SV_i\hat{\hat{\eta}}_{isv}$, $\tilde{\eta}_{ie} = \sigma_{\varepsilon_i}\hat{\hat{\eta}}_{ie}$, and $\hat{\hat{\eta}}_{iec}$, $\hat{\hat{\eta}}_{isv}$ and $\hat{\hat{\eta}}_{ie}$ are functions of *only* CCPs, which are known from the first step estimation. $\tilde{\eta}_{i\pi}$ is a function of both CCPs and firms' revenues, which are also known. The $\boldsymbol{\theta}$ are parameters to be estimated in the second step estimation using BBL. In particular, these parameters have the following relationship:

$$\theta_{i\pi} = \frac{1}{\sigma_{\varepsilon_i}}$$
$$\theta_{iec} = EC_i\theta_{i\pi}$$
$$\theta_{isv} = SV_i\theta_{i\pi} \tag{19}$$

Given the first step estimates of CCPs and the revenue function, we can recover all the θ parameters from equation 18, and the structural parameters can be recovered from

$$\sigma_{\varepsilon_i} = \frac{1}{\theta_{i\pi}}$$
$$EC_i = \frac{\theta_{iec}}{\theta_{i\pi}}$$
$$SV_i = \frac{\theta_{isv}}{\theta_{i\pi}} \tag{20}$$

The EC_i and SV_i estimates are in the same unit as $\tilde{\eta}_{i\pi}$, which is in dollar amount.

D Summary of Model Estimates

Table A3 summarizes the main estimates in the revenue and cost functions. We see that operating in big urban areas with highway/road infrastructure are beneficial for both retail chains.[16] Most importantly, the estimates confirm that rival presence will certainly lead to business-stealing effects, especially so for the incumbent Taco Cabana. There also appear to be some asymmetries in terms of the type of markets the two chains do well in. For example, Taco Cabana appears to generate higher revenue from the Hispanic population, while Chipotle appeals to all the ethnic groups except the Hispanic population. Also, both chains appear to fair poorly in high income areas, though Taco Cabana benefits more from low income areas than Chipotle. Finally, there is a monotonic relationship between age and sales for Taco Cabana, while Chipotle appeals to the youngest and oldest age groups.

Table A4 provides the normalized (i.e., dollar amount) sunk cost estimates from our model. The Appendix provides further details as to how exactly the normalized parameters are obtained, as the procedure we use is slightly more involved than typical approaches. In our case, normalization is possible as sales are observed. These structural estimates reveal that Taco Cabana has noticeably higher entry costs and scrap values than Chipotle (at least 3 times larger). Also worth noting is that the scrap values have a positive sign, which suggests that the chains may be able to recover some (but certainly not all) of the sunk costs upon leaving a market (Taco Cabana more so than Chipotle), say by selling the real estate where their outlets are situated. The fact that the sunk costs are not fully recovered reiterate the fact that exit from a market is costly for both firms. The difference in size between the two chains (as discussed in the data description) could explain why their scrap value and entry costs estimates are markedly different. On this note, we would like to point out that the entry costs and scrap values presented in Table 3 should be scaled up by 33 to reflect the

[16] We note that in these specifications, we do not explicitly include market fixed effects. The inclusion of fixed effects would then preclude our ability to say anything about the impact of various urban features (which do not vary over time). Finally, our simulation results are robust to ranges of parameters for the strategic interactions.

Table A3: Revenue Regression and Sunk Cost Estimates

	Chipotle		Taco Cabana	
	Estimate	Std. Error	Estimate	Std. Error
Revenue function				
Rival presence	-139.7355	0.1147	-1006.2883	0.6024
Population density	-25.7970	0.0858	-60.4747	0.1629
Share population (15-34)	636.7274	0.7130	2821.3028	2.0201
Share population (35-65)	389.7445	1.1975	4205.6197	3.0320
Share population (65 and up)	840.9123	1.0396	5194.5395	4.8534
Share Hispanic population	-28.4433	0.2002	3677.1807	0.6232
Share white population	47.2858	0.2419	-672.7380	1.3834
Share black population	322.2607	0.3600	1000.8932	1.9487
Share asian population	236.0705	0.3664	-1893.6038	1.5322
Inflation adjusted income	3.7097	0.1136	6.2385	0.4431
In big urban area	192.7348	0.2196	144.0055	0.5464
Interstate highway	34.3877	0.1947	352.9724	0.3180
Primary or secondary road	75.6327	0.1343	-244.7565	0.3313
Daily traffic	-5.5834	0.0364	31.5264	0.0873
Cost function				
Entry cost	-13.0987	0.0755	-42.6541	0.1189
Scrap value	1.0387	0.0256	30.5885	0.0000
Variance of error term	0.0010	0.0001	0.0010	0.0000

actual entry costs and scrap values that these firms incur in the real world. This scaling is done because the estimates of these parameters are relative to the size of alcohol sales, which account for 3% of the total profits per period for both firms. Consequently, the entry cost is roughly equal to the first few years' worth of profits (as one might expect).

E Overview of the Homotopy Method

This section provides more details about the homotopy method. Such methods have been used in Besanko et al. (2010), Borkovsky et al. (2010), Borkovsky et al. (2012), and Doraszelski et al. (2021), so we refer the readers to these papers for more of the details about

Table A4: Normalized Cost Estimates in Dollar Amount

	Chipotle	Taco Cabana
Entry cost (EC)	-13100	-42700
Scrap value (SV)	1040	30600
Difference ($EC - SV$)	-12060	-12100

Table A5: Firms' Profits Per State

Firm	State $(0, 0)$	State $(0, 1)$	State $(1, 0)$	State $(1, 1)$
Taco Cabana	\$ 0	\$0	\$3,160.39	\$2,154.10
Chipotle	\$0	\$733.57	\$0	\$593.83
Chipotle's competitive effect on Taco Cabana			\$1,006.29	
Taco Cabana's competitive effect on Chipotle			\$139.74	

implementation and computation.

The homotopy method requires collecting the Bellman equations and optimality conditions for each player in each state. This collection of conditions then yields a system of equations of the form:

$$H(\sigma, \lambda) = 0, \tag{21}$$

where σ is a vector of policies, and H is a an unknown functional. The homotopy parameter is $\lambda \in [0, 1]$, where this parameter maps into the parameters of the model. With this system set up, we are primarily interested in the following equilibrium correspondence:

$$H^{-1} = \{(\sigma, \lambda) | H(\sigma, \lambda) = 0\} \tag{22}$$

With this correspondence, we trace out paths of equilibria in H^{-1} by varying both the policies and the homotopy parameter. The parametric path can be defined as $(\sigma(s), \lambda(s))$, such that $(\sigma(s), \lambda(s)) \in H^{-1}$, where s is an index for the path as represented by a monotonically increasing or decreasing auxiliary variable.

Differentiating $H(\sigma(s), \lambda(s)) = 0$ with respect to s then gives us:

$$\frac{\partial H(\sigma(s), \lambda(s))}{\partial \sigma(s)} \sigma'(s) + \frac{\partial H(\sigma(s), \lambda(s))}{\partial \lambda} \lambda'(s) = 0 \tag{23}$$

This system of equations thus captures the conditions that need to be satisfied in order to remain on the path. One solution that obeys these differential equations is

$$y_i'(s) = (-1)^{i+1} \det \left(\left[\frac{\partial H(y(s))}{\partial y} \right]_i \right) \tag{24}$$

for each differential equation i. Implementation of the homotopy method essentially amounts to numerically solving the differential equations above, whereby an already computed equilibrium can serve as an initial condition. Differential equations are then used to determine each subsequent step along the path.

F Reconciling the Simulation Results About Cost Conditions with the Past Theoretical Literature

To reconcile the difference between our finding and conventional wisdom, we take a closer look at firms' CCPs at each state, as represented by $S = \{(0,0), (0,1), (1,0), (1,1)\}$, across the aggressive and non-preemptive scenarios. The summary statistics for these CCPs at various states are shown in Table A6. Table A7 highlights the difference between firms' aggressive CCPs and non-preemptive CCPs. As shown in Table A7, firms' aggressive CCPs are fairly different from their non-preemptive CCPs at states 1 and 2, where Taco Cabana has no presence. The maximum differences in CCPs for Taco Cabana at states 1 and 2 are 0.035 and 0.093 respectively, and those for Chipotle are 0.047 and 0.012 respectively. However, in states 3 and 4, where Taco Cabana has incumbency, firms' aggressive CCPs are almost the same as their non-preemptive CCPs. This is shown in the last two columns of Table A7, where the maximum difference in CCPs for both firms in state 1 and 2 is in the order of 10^{-5} or less. Despite firms' CCPs being different across preemptive and non-preemptive scenarios, firms' survival rates based on both their density and expected values at the steady state are almost exactly the same for all parameters in the space of entry cost and scrap value. This pattern implies that the steady-state distributions under the aggressive scenario and the non-preemptive scenario are almost identical.

This similarity between steady-state distributions under the preemptive and non-preemptive scenario is caused by the fact that Taco Cabana very rarely exits after entry. As shown in Table A6, Taco Cabana's CCPs in both scenarios are almost 1 at states 3 and 4. This behavior can be rationalized by Taco Cabana's scrap value ($12,100), which is much smaller than its entry cost ($42,700). In a dynamic game with re-entry opportunities, entry cost is relevant to firms' exit decisions. Firms that choose to exit have to consider the potential cost of re-entry. If the entry cost is large, then the opportunity cost of exit is high, and firms would be reluctant to exit. Therefore, Taco Cabana's CCPs at states 3 and 4 are almost 1. Note that this feature is not present in simple multi-stage games, where only scrap values matter for firms' exit decisions (Judd, 1985).

It is easy to derive that with this type of CCP, the steady state distribution would include almost only states 3 and 4, and the probabilities of the other two states are very close to 0. Such a steady-state distribution implies that firms' behaviors at states 3 and 4 ultimately determine its survival rates. Given that Taco Cabana's CCPs at states 3 and 4 are very close to 1 under both the preemptive and non-preemptive scenarios, Taco Cabana's survival rate based on the density measure would be very much the same.

Taco Cabana's survival rate based on the value measure would depend on the extent to which Chipotle behaves differently at states 3 and 4 in the deterrence-motivated entry scenario v.s. the scenario with no deterrence motives. Chipotle would behave differently if there is opportunity for it to deter the entry of Taco Cabana; that is, if Taco Cabana's CCPs are very different at state 3, where Chipotle is not present, compared to how it does at state 4, where Chipotle is present, then Chipotle can enter aggressively at state 3 in hope

Table A6: Firms' Preemptive and Non-Preemptive CCPs by State

Firm	Statistics	State 1	State 2	State 3	State 4
Preemptive CCPs					
Taco Cabana	min	0.3390778	0.1863653	0.9999907	0.9999757
	median	0.8289986	0.1910989	0.9999989	0.9999765
	max	0.8730996	0.7930829	0.9999992	0.9999985
Chipotle	min	0.0000019	0.0031923	0.0000017	0.0030901
	median	0.1388121	0.9992291	0.1190279	0.9984611
	max	0.998289	0.9999996	0.9981367	0.9999991
Non-Preemptive CCPs					
Taco Cabana	min	0.3291699	0.1863609	0.9999899	0.9999757
	median	0.8123915	0.1883983	0.9999987	0.9999761
	max	0.8730991	0.7930388	0.9999992	0.9999985
Chipotle	min	0.0000018	0.0032125	0.0000017	0.0030901
	median	0.1257854	0.998831	0.1190165	0.9984611
	max	0.9983171	0.9999993	0.9981367	0.9999991

Table A7: Difference Between Firms' Preemptive and Non-Preemptive CCPs by State

Firm	Statistics	State 1	State 2	State 3	State 4
Taco Cabana	min	0.00000045	0.00000441	0.00000000	0.00000000
	median	0.00468267	0.00118247	0.00000008	0.00000008
	max	0.03507923	0.09314385	0.00000103	0.00000604
Chipotle	min	-0.00280884	-0.00384164	-0.00000011	-0.00000015
	median	0.00087871	0.00003658	0.00000064	0.00000001
	max	0.04746761	0.01221447	0.00001279	0.00000243

to push out Taco Cabana at state 4. However, as shown in Table A6, Taco Cabana's CCPs at state 4 is only slightly smaller than those at state 3 because Taco Cabana's small scrap value forces Taco Cabana to stay in the market after entry with an almost 1 probability. This minuscule difference in Taco Cabana's strategy across Chipotle's incumbency states leaves very little room for Chipotle to employ a deterrence strategy on Taco Cabana, and that explains why Chipotle's CCPs under the preemptive scenario are almost identical to those under the scenario with no deterrence-motivated entry in states 3 and 4 (as shown in both Table A6 and Table A7). In other words, Chipotle behaves the same across these two scenarios at states 3 and 4. Given this finding, the steady-state distribution would be almost identical across the preemptive and non-preemptive scenarios, and Taco Cabana's value-based survival rates would also be very much the same in different scenarios.