The Dynamics of Retail Oligopoly

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Abstract

This paper examines competition between supermarkets as a dynamic discrete game between heterogeneous players. We focus on the impact of Wal-Mart's entry on incumbent supermarket firms, quantifying the impact on welfare and competition. Employing a unique thirteen year panel dataset of store level observations that includes every supermarket firm operating in the United States alongside the rapid proliferation of Wal-Mart supercenters, we propose and estimate a dynamic structural model of chain level competition in which incumbent firms choose each period whether to add or subtract stores or exit the market entirely, and potential entrants choose whether or not to enter. Product market competition is modeled as Nash in prices, incorporating detailed information on prices and characteristics and unobserved heterogeneity in chain-level quality. Our estimation approach combines two-step estimation methods with a one-period ahead (renewal) representation of the value function. This structure serves several purposes. First, it allows us to accommodate a continuous state space, which is essential given the wide range of markets in which supermarket firms compete. Second, it allows for a certain form of incompleteness in the sampling scheme, stemming from the fact that Wal-Mart has yet to exit a market or close a supercenter. Finally, it allows us to include structural errors for all actions, including investment. Using the results from the structural estimation, counterfactuals quantifying the welfare impact of Wal-Mart's entry are performed using an extension of the Pakes and McGuire (2001) stochastic algorithm.

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1 Introduction

Retail firms account for a surprising fraction of economic activity. In particular, retailers employ over 20% of the private sector workforce and produce nearly 13% of US GDP. Furthermore, mass merchandisers like Wal-Mart and Target have led the way in developing and diffusing innovative information technologies, often forcing upstream producers to lower prices and make complementary cost reducing investments. The rise of the "big box" format and a continued emphasis on one stop shopping has both increased the variety of products and lowered their costs. At the same time, many retail industries have become highly concentrated. Most "category killers" now compete locally with only one or two rivals. In some categories, like office supplies, there are only two or three chains nationwide. Viewed more broadly, these industries exhibit a highly skewed size distribution: a few giant chains compete with a large number of small local players. While the explosion in variety and reduction in price is unambiguously beneficial to consumers, the increase in concentration may be cause for concern. Fear of increased in concentration and impact on small businesses has triggered many municipalities to pass zoning laws restricting entry of "big-box" stores to their markets. The goal of this paper is to develop a model of retail chain competition in which the impact of restrictions on competition between retail chains on competition, prices and consumer and total welfare can be evaluated.

The theoretical framework proposed in this paper is based on the Markov perfect equilibrium (MPE) framework of Ericson and Pakes (1995), in which firms make competitive investments that increase the quality of their products. In the context of retail competition, in which firms operate a chain of individual stores, quality is a function of the total number of stores operated by each firm, the individual characteristics of their stores, and their overall format (conventional supermarket or Supercenter). Allowing firms to adjust all of these features independently would yield an intractably complex control problem. Instead, our strategy is to focus on a single dimension of quality (store density) and allow firms to differ by format (supermarket or Supercenter). Product market competition is modeled using a discrete choice model of demand, in which firms may also differ by a measure of "perceived" quality that is fixed over time. We assume that the economically relevant features of the industry can be encoded into a state vector that includes each firm's store density, its overall format, and its perceived level of quality. Firms receive state dependent payoffs in the product market and influence the evolution of the state vector through their entry, exit, and investment decisions. In particular, firms can adjust their chain size each period by either opening new stores or closing existing ones. Equilibrium occurs when firms choose strategies that maximize their expected discounted profits, given the expected actions of their rivals.

We estimate this model of competition using a unique panel dataset that follows the entire supermarket industry over thirteen consecutive periods (years). Our estimator is based on the two-step procedure proposed by Aguirregabiria and Mira (2007), using an alternative representation of the value function suggested by Arcidiacono and Miller (2008). In the first step, we recover the firm's policy functions governing entry, exit, and investment. These functions characterize firms beliefs regarding the evolution of the common state variables and the actions of their competitors. We also estimate the per-period payoff that each firm receives as a function of the current state. In the second step, we use the structure of the MPE to recover the parameters that make those beliefs optimal. Following Hotz and Miller (1993), this is accomplished by replacing the continuation values in the best response probability functions with inverted conditional choice probabilities (CCPs) that can be recovered non-parametrically from the data. To accommodate our large state space and rich choice set, we use Monte Carlo simulation to construct these "nuisance" parameters, and estimate the structural parameters using simulated pseudo maximum likelihood. Having recovered the structural parameters of the underlying model, we then perform policy experiments aimed at evaluating the impact of zoning laws that prevent the growth of Supercenters on investment, market structure, and consumer and producer surplus, using a discrete control version of the Pakes and McGuire (2001) stochastic algorithm.

This paper builds on both the sizable empirical literature on static entry games as well as more recent work on dynamic games. Until recently, the empirical entry literature has mainly employed static models of competition. As a consequence, the early papers were somewhat limited in scope, focusing primarily on characterizing the number of firms that could fit into markets of various size. In a series of seminal papers, Bresnahan and Reiss examined the relative importance of strategic and technological factors in determining market structure (Bresnahan and Reiss (1987, 1990, 1991)). By comparing the threshold market size at which only a single firm could survive to that which could sustain a second entrant, the authors were able to distinguish empirically between the impact of sunk costs and the role of price competition. Berry (1992) extended this analysis to include both heterogeneity across firms and the impact of firm characteristics. More recently, Mazzeo (2002) and Seim (2006) have extended the static approach to incorporate various aspects of product differentiation, documenting the empirical relevance of both location and quality. In all of these studies, firms are assumed to provide only a single product. More importantly, a static setting clearly limits our ability to evaluate either merger policy or changes in the environment, as these are fundamentally dynamic questions. The emphasis on static (really two-period) frameworks was a direct result of the complexity associated with estimating a fully dynamic model of competition. Until recently, the burden was virtually insurmountable, as estimation required solving explicitly for an MPE via a nested fixed-point procedure that placed very strong restrictions on the size of the state space. This computational burden placed severe restrictions on the ability to model complex interactions. However, the application of two-step estimation techniques has eased the burden substantially (Aguirregabiria and Mira (2007), Bajari, Benkard, and Levin (2007), Pakes, Ostrovsky, and Berry (2007), and Pesendorfer and Schmidt-Dengler (2007)), opening the door to much more realistic competitive frameworks.[1] Our goal is to use these methods to estimate a fully dynamic model of entry in which firms are able to adjust their level of quality each period. Our paper is closest to the work of Ryan (2004), who estimates a dynamic model of entry and investment in the cement industry. Using a panel of firms in geographically distinct markets, he is able to recover the full cost structure of the industry and evaluate the welfare impact of a change in environmental policy. Other notable applications of two-step estimation techniques include Collard-Wexler (2006), Dunne, Klimek, Roberts, and Xu (2006), and Sweeting (2007).

The paper is organized as follows. Section 2 describes the construction of the dataset. Section 3 describes the theoretical framework. The empirical framework is described in Section 4. The results of the first and second steps of the estimation are presented in Section 5, while the results of the policy experiments (TBD) will be contained in Section 6. Section 7 concludes.

[1] See Benkard (2004) for an early application of these methods to learning and strategic pricing in the commercial aircraft industry.

2 Data

The data for the supermarket industry are constructed from yearly snapshots of the Trade Dimension's Retail Tenant Database spanning the years 1994 to 2006, while market specific population growth rates are taken from the U.S. Census. Trade Dimensions collects store level data from every supermarket operating in the U.S. for use in their *Marketing Guidebook* and *Market Scope* publications, as well as selected issues of *Progressive Grocer* magazine. The data are also sold to marketing firms and food manufacturers for marketing purposes. The (establishment level) definition of a supermarket used by Trade Dimensions is the government and industry standard: a store selling a full line of food products and generating at least \$2 million in yearly revenues. Foodstores with less than \$2 million in revenues are classified as convenience stores and are not included in the dataset. Firms in this segment operate very small stores and compete with only the smallest grocery stores.

Information on average weekly volume, store size, number of checkouts, number of employees (full time equivalents), and the overall format of the store (e.g. Supercenter or conventional supermarket) is gathered through quarterly surveys sent to store managers. These surveys are then compared with similar surveys given to the principal food broker assigned to each store and further verified via repeated phone calls. Each store is assigned a unique identifier code that remains with the store regardless of ownership, which we used to construct the overall panel. In addition, each store has a unique *firm* code, which we used to identify the ultimate owner. The availability of reliable firm identifiers is critical in the supermarket industry since parent firms will often operate stores under several "flag names," especially when the stores have been acquired by merger. Initially, to avoid problems of false exits and entries, we treat stores acquired in a merger as having always belonged to their final owner. Also, when a firm is taken private or bought out by a public holding company, we do not treat the event as an entry (or exit).

Previous empirical studies of the supermarket industry suggest dividing the retail food market into two distinct submarkets: supermarkets and grocery stores (Ellickson (2007), Smith (2004)). Supermarkets compete in a tight regional oligopolies that do not compete significantly with the much smaller and highly fragmented grocery segment. Furthermore, the number of firms in these oligopolies do not increase with market size, yielding an equilibrium that is apparently stationary with respect to population growth. Our retail database includes both types of firms. Since we are primarily concerned with competition between retail oligopolists and require a market structure that is stationary, we focus only on the "top" firms in each market. Specifically, we include in our panel only those firms that served at least 5% of the market (MSA) in which they operated in at least one period. Because the top supermarket firms do not compete significantly with the grocery firms in the fringe,[2] this should not introduce any selection problems.

The discrete choice model we use to characterize product market competition requires us to specify and collect data on the sales of the outside good. Obvious consumer alternatives to supermarkets include grocery stores, convenience stores, liquor stores, restaurants, and cafeterias. Therefore, we assume that total sales of the outside good are equal to the combined sales of all food and beverage stores (NAICS 445 - of which supermarkets are a subset) and all foodservice and drinking establishments (NAICS 772) less the sales accounted for by supermarkets alone. Data on total sales is taken from the 1997 Census of Retail Trade. To construct the share of the outside good, we use the Census dataset to construct an MSA specific multiplier characterizing the ratio of total sales in both categories (445 and 772) to total sales in supermarkets alone (NAICS 44511). We then use this multiplier to impute the total sales in both categories for each MSA in our dataset, using the observed revenue of the supermarkets as our baseline measure of sales. We are implicitly assuming that the ratio is constant over time.

Estimating this demand system also requires data on firm level prices, which we acquired from the American Chamber of Commerce Researchers Association (ACCRA). The ACCRA collects data from over 250 U.S. towns and cities on the prices of various retail products (26 of which are grocery items) for use in the construction of their *Cost of Living Index*. The ACCRA sends representatives to several supermarkets in each geographic market with the goal of collecting a representative sample of prices at the major chains. They are given a specific list of products for which to collect individual prices (e.g. 50 oz. Cascade dishwashing powder). We purchased their disaggregated dataset, so we observe the store name and individual prices for each product. We then use these individual prices to construct a price index (using the same weights employed by ACCRA) for each store in

[2] Ellickson (2006) and Smith (2004) both present empirical results that support this claim.

their dataset that is inflated to match average weekly grocery expenditures, as reported by the BLS. Since we are modeling competition at the firm level, we then aggregated these indices up to the level of the firm (in each market) and matched them to the corresponding firms in our panel, yielding a total of 649 MSA/firm level observations on price. Since ACCRA only began recording the names of the individual stores in 2004, we have prices for only a single period. Summary statistics are provided in Table 1.

Table 1: Summary Statistics

	Format	
	Supercenter	Supermarket
Store Size	65.2 (22.8)	36.3 (15.2)
Checkouts	29.4 (6.36)	10.1 (3.94)
Stores per Market	3.64 (5.48)	10.4 (22.6)
Market Share	16.6 (13.9)	15.1 (10.2)
Basket Price	82.08 (6.31)	95.66 (10.28)
Firms per MSA	.70 (.64)	4.38 (1.42)

Store size is in 1000s of square feet.

Table 2: Action Frequencies

	Potential Entrants			Incumbents	
	Supercenter	Supermarket		Supercenter	Supermarket
Don't Enter	93.5%	92.9%	Exit	1%	2.7%
Build 1	5.3%	6.1%	Close 2+		2.5%
Build 2	1.2%	.6%	Close 1		6.3%
Build 3		.4%	Do Nothing	71%	74%
			Open 1	18%	9%
			Open 2+	10%	5.2%

3 Model

Our model of competition between retail chains is based on the Ericson and Pakes (1995) dynamic oligopoly framework. A notable difference is that all controls are discrete in our setting, as the relevant unit of investment is a single store. For this reason, our game fits nicely within the framework of Aguirregabiria and Mira (2007) as well. The game is in discrete time with an infinite horizon. We observe M distinct geographic markets ($m = 1, .., M$), taken here to be the 276 U.S. Metropolitan Statistical Areas (MSAs), but suppress the market subscript in what follows. For each market/period combination, we observe a set of incumbent firms who are currently active in the market. Firms differ by format (type), either conventional supermarket or Supercenter (e.g. Wal-Mart and Target), and we assume that all outlets operated by a particular firm are of a single format. We further assume the existence of two potential entrants per period, one of each type, who choose whether or not to enter the market in that period. If they choose not to enter, they are replaced by new potential entrants in the subsequent period.

We follow closely the notation of Aguirregabiria and Mira (2007), noting differences as they arise. We assume that N firms can either operate or potentially enter the market each period. The set of active firms are called incumbents, and the remaining firms potential entrants. If the market currently contains less than N firms, at most two of the potential entrants (one of each type) may enter each period. We index firms by $i \in I = \{1, 2, ..., N\}$. Each period, incumbent firms choose whether to add or delete stores, do nothing, or exit the market entirely. Potential entrants choose whether or not to enter, and how many stores to build. However, we suppress the distinction between potential entrants and incumbents in the general set-up of our model, re-visiting the distinction when we introduce the empirical framework. The firms' discrete and finite choice set is denoted $A = \{0, 1, ..., J\}$, a typical element of which is a_{it}. Note that, in our application, the choice set depends on the current number of stores a firm currently operates (i.e. their current state), but we write it more parsimoniously here to conserve notation. The vector of all firm's current actions is given by $a_t = (a_{1t}, a_{2t}, ..., a_{Nt})$. In each period, a firm is characterized by two vectors of state variables, x_{it} and ε_{it}, while the market conditions (e.g. population) are described by the vector y_t. The vectors x_{it} and y_t are common knowledge of all firms, while ε_{it} is only known by firm i, making this a game of incomplete information. Each vector x_{it} is composed of three elements: the firm's type (assigned upon entry), its perceived quality (assigned upon entry and fixed over time), and its "store density" (the number of stores it operates per capita).[3]

Collecting terms, $x_t \equiv (y_t, x_{1t}, x_{2t}, ..., x_{Nt})$ and $\varepsilon_t \equiv (\varepsilon_{1t}, \varepsilon_{2t}, ..., \varepsilon_{Nt})$ are then the vectors of commonly and privately observed state variables, respectively. Firm i's per period profit function is given by $\tilde{\Pi}_i (a_t, x_t, \varepsilon_{it})$. We further assume that $\{x_t, \varepsilon_t\}$ follows a controlled Markov process with known transition probability $p(x_{t+1}, \varepsilon_{t+1}|a_t, x_t, \varepsilon_t)$. Assuming that firms share a common discount factor β, firms choose actions to maximize expected discounted profits

$$E\left\{\sum_{s=t}^{\infty} \beta^{s-t}\tilde{\Pi}_i (a_s, x_s, \varepsilon_{is}) |x_t, \varepsilon_{it}\right\}. \tag{1}$$

Following Aguirregabiria and Mira (2007), we make the following three assumptions on the primitives of the model.

Assumption 1 (AM, 2007) - *Additive Separability*: Private information appears additively in the profit function. That is, $\tilde{\Pi}_i (a_t, x_t, \varepsilon_{it}) = \Pi_i (a_t, x_t) + \varepsilon_{it} (a_{it})$, where $\Pi_i (\cdot)$ is a real-valued function and $\varepsilon_{it} (a_{it})$ is the $(a_{it} + 1)\,th$ component of the $(J + 1) \times 1$ vector ε_{it} with support R^{J+1}.

Assumption 2 (AM, 2007) - *Conditional Independence*: The transition probability $p(\cdot|\cdot)$ factors as $p(x_{t+1}, \varepsilon_{t+1}|a_t, x_t, \varepsilon_t) = p_\varepsilon(\varepsilon_{t+1})f(x_{t+1}|x_t, a_t)$. That is, (i) given the firms' decisions at period t, private information variables do not affect the transition of common knowledge variables, and (ii) private information variables are independently and identically distributed over time.

Assumption 3 (AM, 2007) - *Independent Private Values*: Private information is independently distributed across players, $p_\varepsilon(\varepsilon_t) = \prod_{i=1}^N g_i (\varepsilon_{it})$, where, for any player i, $g_i(\cdot)$ is

[3] The class of dynamic models we use for both estimation and simulation require state variables that remain stationary. Although population is free to grow without bound and the number of stores operated by the most successful chains rarely decreases, the number of stores per capita is relatively stable. Furthermore, due to the importance of endogenous fixed investments (Ellickson (2007)), the number of firms is also quite stable, both over time and across markets. In particular, we believe that the dynamics of retail chain growth can be modelled using a pure vertical differentiation model like Pakes and McGuire (1994) where the "improvement in the outside good" corresponds to increases in population. If a firm does not invest to counteract population growth, its "quality" (i.e. store denstiy) will deteriorate relative to its rivals and it will eventually be forced to exit.

a density function that is absolutely continuous with respect to the Lebesgue measure.

We further assume that $g_i(\cdot)$ is the pdf of the type I extreme value (T1EV) distribution. Note that we do *not* require the fourth assumption imposed by Aguirregabiria and Mira (2007), that the common knowledge variables have discrete and finite support, because we employ an alternative method (due to Arcidiacono and Miller (2008)) to construct continuation values.

We assume that firms play stationary Markov strategies, allowing us to suppress the time subscripts in what follows. We focus only on pure strategy Markov Perfect Equilibrium (MPE) and restrict attention to equilibrium strategies that are symmetric and anonymous (exchangeable). A Markov strategy for firm i is then a mapping from states into actions $\sigma_i : X \times R^{J+1} \to A$ and a strategy profile is a vector $\sigma = \{\sigma_i(x, \varepsilon_i)\}$. Given σ, we further define the set of conditional choice probabilities (CCPs) $P^\sigma = \{P_i^\sigma(a_i|x)\}$ such that

$$P_i^\sigma(a_i|x) \equiv \Pr(\sigma_i(x,\varepsilon_i) = a_i|x) = \int I\{\sigma_i(x,\varepsilon_i) = a_i\}\, g_i(\varepsilon_i)\, d\varepsilon_i. \tag{2}$$

where $I(\cdot)$ is the indicator function. Let the deterministic component of per period profit from the (static) product market competition stage (including any investment payoffs or costs) be given by $\pi_i^\sigma(a_i, x)$. We further parameterize this profit function below (when we discuss product market competition), but leave it unspecified for now. Because the private information components of the state vector are independent,

$$\pi_i^\sigma(a_i, x) = \sum_{a_{-i} \in A^{N-1}} \left(\prod_{j \neq i} P_j^\sigma(a_{-i}[j]\,|x) \right) \Pi_i(a_i, a_{-i}, x),$$

where $a_{-i}[j]$ is the j^{th} firm's element of the vector of rival firms' actions a_{-i}. Let $\tilde{V}_i^\sigma(x, \varepsilon_i)$ be the (optimal) value of firm i given that all other firms follow strategy profile σ. Using Bellman's (1957) recursive representation, we can then write

$$\tilde{V}_i^\sigma(x,\varepsilon_i) = \max_{a_i \in A} \left\{ \pi_i(a_i, x) + \varepsilon_i(a_i) + \beta \int_{x'} \left[\int \tilde{V}_i^\sigma(x', \varepsilon_i')\, g_i(\varepsilon_i')\, d\varepsilon_i' \right] f_i^\sigma(x'|x, a_i) \right\}, \tag{3}$$

where $f_i^\sigma(x'|x, a_i)$ is the transition probability of x conditional on firm i choosing a_i and the other firms following σ :

$$f_i^\sigma(x'|x, a_i) = \sum_{a_{-i} \in A^{N-1}} \left(\prod_{j \neq i} P_j^\sigma(a_{-i}[j]\,|x) \right) f(x'|x, a_i, a_{-i}).$$

It is useful to write the ex ante value function $V_i^{\sigma}(x)$, which is integrated over private information and given by $V_i^{\sigma}(x) = \int \tilde{V}_i^{\sigma}(x, \varepsilon_i)\, g_i(d\varepsilon_i)$. This is equivalent to

$$V_i^{\sigma}(x) = \int \max_{a_i \in A} \{v_i^{\sigma}(a_i, x) + \varepsilon_i(a_i)\}\, g_i(d\varepsilon_i), \tag{4}$$

where $v_i^{\sigma}(a_i, x) \equiv \pi_i(a_i, x) + \beta \int_{x'} V_i^{\sigma}(x')\, f_i^{\sigma}(x'|x, a_i)$ is referred to as a *choice specific* value function. A stationary Markov perfect equilibrium is then a set of strategy functions σ^* such that for any firm i and any $(x, \varepsilon_i) \in X \times R^{J+1}$,

$$\sigma_i^*(x, \varepsilon_i) = \arg\max_{a_i \in A} \{v_i^{\sigma}(a_i, x) + \varepsilon_i(a_i)\}. \tag{5}$$

Aguirregabiria and Mira (2007) note that it is also possible to represent MPE in probability space, which is key to implementing their two-step estimation procedure. Let σ^* be a set of MPE strategies and P^* the probabilities associated with those strategies, such that $P_i^*(a_i|x) = \int I\{a_i = \sigma_i^*(x, \varepsilon_i)\}\, g_i(\varepsilon_i)\, d\varepsilon_i$. The equilibrium probabilities are a fixed point, $P^* = \Lambda(P^*)$, where for any probability vector P, $\Lambda(P) = \{\Lambda_i(a_i|x; P_{-i})\}$ and

$$\Lambda_i(a_i|x; P_{-i}) = \int I\left(a_i = \arg\max_{a_i \in A}\left\{v_i^{P^*}(a_i, x) + \varepsilon_i(a_i)\right\}\right) g_i(d\varepsilon_i). \tag{6}$$

The slight change in notation (the superscript P^* instead of σ) is used to emphasize the fact that the conditional value functions (along with the profit and transition functions) depend on σ only through P. The functions Λ_i are called best response probability functions. The equilibrium probabilities P^* solve the coupled fixed point problem defined by (4) and (6). Existence of equilibrium follows directly from Brouwer's fixed point theorem, but uniqueness is not likely to hold in general. Doraszelski and Satterthwaite (2009) provide a detailed discussion of existence and uniqueness in a similar class of models.

Notice that equation (6), which characterizes equilibrium choice probabilities, has the structure of a standard static discrete choice problem (a conditional logit, for example, if the ε's are distributed T1EV). The complication, relative to the static setting, is that we do not have a closed form representation for $v_i^{P^*}(a_i, x)$, the analog of the mean utilities in the static choice problem. Recall that these choice specific value functions are composed of two terms: the per period profit function (whose functional form is typically specified) and the continuation value (whose functional form is defined recursively via the Bellman equation). It is this second term which is problematic. The idea behind two-step estimation is to replace the second term with a function of the data, treat this as a nuisance parameter in estimation, and use (6) to build a pseudo likelihood function to recover the structural parameters of the profit function.[4] Aguirregabiria and Mira (2007) rely an alternative representation of (6) that allows the continuation value to be replaced by the solution to a system of linear equations, which is why they require a finite support condition on the observed state variables. We utilize an equivalent representation (due to Arcidiacono and Miller (2008)) that does not require inverting a matrix, allowing us to relax the finite support assumption and accommodate a much larger state space.

First, note that since we have assumed that the ε's are distributed T1EV, the equilibrium choice probabilities can be calculated directly using the well-known logit formula

$$P_i^*\left(a_i|x\right) = \frac{\exp\left(v_i^{P^*}\left(a_i,x\right)\right)}{\sum\limits_{a_i\in A}\exp\left(v_i^{P^*}\left(a_i,x\right)\right)}. \tag{7}$$

More importantly, because the integral with respect to $g_i\left(\cdot\right)$ can now be computed analytically, the choice specific value function can be re-written as follows (c.f. McFadden (1984))

$$v_i^{P^*}\left(a_i,x\right) = \pi_i\left(a_i,x\right) + \beta\int\limits_{x'}\ln\left[\sum_{a_i'\in A}\exp(v_i^{P^*}\left(a_i',x'\right))\right] f_i^{\sigma}(x'|x,a_i). \tag{8}$$

As demonstrated in Arcidiacono and Miller (2008), this representation is equivalent to the

[4] There are three main methods for substituting out the continuation value term in the choice specific value function (Miller (1997)). The first is to use the recursive structure of the Bellman equation to solve for the value function as the solution of a system of linear equations. This is the "policy evaluation" approach is used in Aguirregabiria and Mira (2007), but it requires inverting a matrix (and therefore places a limit on the size of the problems that can be evaluated). The second method, which was originally proposed by Hotz, Miller, Sanders, and Smith (1994), uses forward simulation to approximate the continuation value (as a large but finite sum of expected payoffs). This approach, extended by Bajari, Benkard, and Levin (2007), can handle much larger problems, along with continuous controls. The third approach, due to Hotz and Miller (1993), exploits that fact that in problems where there is a terminating action (like exit), the choice specific value functions can be represented purely as a function of conditional choice probabilities and the one-time terminal payoff, eliminating the dependence on future values. Altug and Miller (1998) extend this approach to a class of problems that exhibit "finite dependence". See Arcidiacono and Miller (2008) for a detailed discussion of this class.

following

$$\begin{aligned} v_i^{P^*}(a_i,x) = \quad & \pi_i(a_i,x) - \beta \int\limits_{x'} \ln\left[P_i^*(a_i'=0|x')\right] f_i^{\sigma}(x'|x,a_i) \\ & + \beta \int\limits_{x'} v_i^{P^*}(a_i'=0,x')) f_i^{\sigma}(x'|x,a_i), \end{aligned} \tag{9}$$

where the required normalization is made with respect to a single (arbitrary) choice.[5] Note that (9) only depends on the choice probability and continuation value of this one baseline alternative. In general, this is not especially helpful since there is still a continuation value on the right hand side of (9). However, in the case of a terminating action (like exit), it is extremely useful, since a terminating action has no future implications beyond its current payoff. Thus, its continuation value is simply its current payoff, which typically has a known functional form, just as any other per period payoff. In particular, this means that both the first and third terms on the right hand side of (9) will be known (up to a vector of parameters) and the second term is simply a function of the data, provided that the value functions are normalized with respect to a terminating action (i.e. exiting). Therefore, the MPE is a fixed point of the mapping $\Psi(P) = \{\Psi_i(a_i|x;P)\}$ with

$$\begin{aligned} \Psi_i(a_i|x;P) = \quad & \int I\Bigg(a_i = \arg\max_{a\in A} \{\pi_i(a,x) + \varepsilon_i(a) \\ & - \beta \int\limits_{x'} \ln\left[P_i^*(a_i'=0|x')\right] f_i^{P^*}(x'|x,a) \\ & + \beta \int\limits_{x'} \pi_i(a_i'=0,x')) f_i^{P^*}(x'|x,a_i)\ \} \Bigg) g_i(d\varepsilon_i). \end{aligned} \tag{10}$$

This expression no longer contains a continuation value and can therefore be used directly in constructing a pseudo likelihood function.

[5] Note that this representation does not require that the ε's be distributed T1EV. However, a distribution from the GEV family (e.g. T1EV, nested logit, PDGEV) does deliver a convenient analytic form for the CCP inversion (see Arcidiacono and Miller (2008) for details).

3.1 Estimation

Our dataset is a panel covering $M = 276$ geographic markets over $T = 13$ periods. Given this short panel structure, asymptotics are in the number of markets M. The pseudo likelihood function can be written as

$$Q_M(\theta, P) = \frac{1}{M} \sum_{m=1}^{M} \sum_{t=1}^{T} \sum_{i=1}^{N} \ln \Psi_i \left(a_{imt} | x_{mt}; P, \theta\right), \tag{11}$$

where P is an arbitrary vector of choice probabilities. Given a consistent first stage estimate $\hat{P}^0$ of the population probabilities P^0, the two-step pseudo maximum likelihood (PML) estimator is then

$$\hat{\theta}_{2S} \equiv \arg\max_{\theta \in \Theta} Q_M \left(\theta, \hat{P}^0\right). \tag{12}$$

where $2S$ stands for two-step. Aguirregabiria and Mira (2007) establish root-M consistency and asymptotic normality of the PML estimator under standard regularity conditions, and derive analytic formulae for calculating standard errors. They also propose a recursive extension of the two-step PML estimator, the nested pseudo likelihood estimator (NPL), that does not require consistent first stage estimates of P^0 and, if it converges, converges to the full-information maximum likelihood estimator (i.e. the nested fixed point estimator of Rust (1987)). In our context, this extension is important, since the exit probabilities are undoubtedly estimated with a fair amount of noise (as exit is a relatively low probability event).

Three complications arise in our setting relative to Aguirregabiria and Mira (2007). First, given the size of the choice set (up to eight options for incumbent firms, four for potential entrants) and the number of active players (up to seven), we cannot explicitly calculate the full set of permutations of x' (the possible market structures, one period ahead) that appear on the right hand size of (9). Instead, using an approach analogous to Monte Carlo integration, we use simulation to approximate these sums. Second, since our state variables have continuous support (or, at the very least, can take many values), we also cannot simply "read the choice probabilities" off the data (e.g. by using a bin estimator), as the choice probabilities that enter the right hand side of (9) are for the next period ahead (they are not, in general, in the support of the observed data). These choice probabilities are used in (10) both to construct the exit probabilities and the "weights" represented by the transition kernel's $f(\cdot)$ that appear in the second and third terms. We simply interpolate these values using flexible semi-parametric methods, which is analogous to using smoothing parameters to compensate for the sparse coverage of a finite dataset.

The third complication involves the structure of competition in this industry. While the supermarket format is a mature category, the supercenter is a relatively new phenomenon.[6] The first Wal-Mart supercenter opened in 1988 and the format grew rapidly from there. Supercenters are clearly still in their expansion phase: Wal-Mart has only closed (really remodeled) a few stores and has yet to exit any market. The same is true for Target. For this reason, we cannot hope to recover the full set of structural parameters for the supercenter firms (i.e. we can't estimate the scrap values associated with either closing stores or exiting markets). We can, of course, still estimate the structural parameters that govern product market competition for both type of firms, so we are able to calculate measures of consumer surplus (both with and without supercenters). However, when it come to estimating the dynamic parameters that characterize investment, we focus on supermarkets alone. Note that we can still perform our counterfactual experiments, since these involve solving for a new equilibrium in which only supermarket firms compete (i.e. supercenters have been eliminated).

4 Empirical Framework

In this section, we describe our empirical framework. First, we decompose per period profits into two terms: the variable profits accrued in the product market and the costs of choosing the discrete action a_i. After specifying the form of the payoff function, we describe the model of product market competition that characterizes the per period stage game. Here we specify a static differentiated products discrete choice demand system and assume that price competition is Nash in prices. We estimate the model using a standard approach, and then calculate per period profits $(\Pi_i(a_i, a_{-i}, x))$ throughout the state space by solving for equilibrium prices and quantities.

Recalling that per period profits are denoted $\Pi_i(a_i, a_{-i}, x)$, we factor these payoffs

[6] The supermarket format dates back to the early 1920s, but didn't fully diffuse into America's suburbs until the 1950s and 60s, when the construction of the interstate highway system finally took shape. Although there were some early precursors to the supercenter as far back as 1930, it was not until the introduction of the first Wal-Mart supercenter in 1988 that the format really took off.

into two components: the variable profits accrued in the product market and the costs of choosing the discrete action a_i. In particular, we assume that

$$\Pi_i\left(a_i, a_{-i}, x\right) = \Pi_i^{PM}\left(a_i, a_{-i}, x\right) + cost(a_i),$$

where $\Pi_i^{PM}\left(a_i, a_{-i}, x\right)$ is the profit from competing in the product market, described below, and $cost(a_i)$ is the cost of action a_i.[7] The relevant "cost" of investment depends on whether the firm is an incumbent or potential entrant, whether it is opening or closing stores, and whether it has chosen to exit. In particular, for incumbent firms

$$cost(a_i) = \begin{cases} \theta_{sell,a_i} & for\ a_i = -3,-2,-1 \\ 0 & for\ a_i = 0 \\ -\theta_{build,a_i} & for\ a_i = 1,2,3 \\ \theta_{scrap,1} + \theta_{scrap,2} \cdot store_i & for\ a_i = \ exit \end{cases}, \tag{13}$$

where θ_{sell,a_i} represents the (positive) payoff associated with selling a_i stores (up to three), $-\theta_{build,a_i}$ is the (negative) cost of building a_i stores (up to three), $\theta_{scrap,1}$ is a fixed scrap payment associated with exiting the market and $\theta_{scrap,2}$ is a marginal (per store) payment that depends in the number of stores being closed upon exit ($store_i$). Taking no action (keeping the same number of stores) requires no incremental investment. Similarly, for potential entrants

$$cost(a_i) = \begin{cases} 0 & for\ a_i = \text{ don't enter} \\ -\theta_{build,a_i} & for\ a_i = 1,2,3 \end{cases}, \tag{14}$$

where the parameters are defined similarly to those of incumbents. Note that this allows for a fully flexible cost function in the level of investment. Having specified the structure of costs, we now describe the construction of $\Pi_i^{PM}\left(a_i, a_{-i}, x\right)$, which involves specifying a static demand system, price setting mechanism, and static equilibrium concept.

Competition in each period is modeled using a standard differentiated products demand model in which consumers have unit demand for a weekly shopping trip. Suppressing the market subscript for brevity, consumer i's conditional indirect utility from shopping at firm j in period t is given by

$$u_{ijt} = z_{jt}\beta - \alpha p_{jt} + \xi_j + \Delta\xi_{jt} + \epsilon_{ijt}, \tag{15}$$

[7] Note that we are implicitly assuming that the cost of opening (or closing) additional stores is not a function of the current state (i.e. it is not cheaper for a bigger chain to open a store). This is perhaps reasonable since the primary scale economies associated with chain size are mostly operational (e.g. quantity discounts on products, the ability to spread advertising outlays across outlets, and the cost synergies associated with utilizing a hub and spoke distribution system).

where z_{jt} is a (2-dimensional) vector of observed firm characteristics, p_{jt} is the price charged by firm j in period t, ξ_j is the mean of the unobserved characteristics of firm j that remains constant over time (its "perceived quality"), $\Delta\xi_{jt}$ is a component of the unobserved firm characteristic that varies over time, and ϵ_{ijt} is an *iid* "logit" error (i.e. T1EV with unit scale). The characteristics we observe for each firm include the number of stores they operate per capita (i.e. their store density d_{jt}) and the firm's format ($type_j$), which is either conventional supermarket or supercenter.[8] We also recover the firm fixed effects $\left(\xi_j\text{'s}\right)$ and use them as a measure of quality. We treat the remaining (time varying) component as an *iid* shock.

Following Berry (1994), we represent the mean utility of firm j in period t as

$$\delta_{jt} = z_{jt}\beta - \alpha p_{jt} + \xi_j + \Delta\xi_{jt} \tag{16}$$

and estimate the parameters β and α using a "Berry logit" IV regression. In particular, given the assumption that the error term ϵ_{ijt} is extreme value, the market share of firm j in period t is given by the familiar logit formula

$$\mathcal{S}_{jt} = \frac{e^{z_{jt}\beta - \alpha p_{jt} + \xi_j + \Delta\xi_{jt}}}{1 + \sum_{k=1}^{J} e^{z_{kt}\beta - \alpha p_{kt} + \xi_k + \Delta\xi_{kt}}}. \tag{17}$$

Normalizing the utility of the outside good to zero and constructing the ratio of shares yields the following estimating equation for the demand parameters:

$$\ln(\frac{\mathcal{S}_{jt}}{\mathcal{S}_{0t}}) = z_{jt}\beta - \alpha p_{jt} + \xi_j + \Delta\xi_{jt}. \tag{18}$$

In order to proceed to estimation, we must construct the share of the outside good, which is taken here to be all food and beverage stores and foodservice and drinking establishments (NAICS 445 and 772) that are not supermarkets. Shares are then constructed as revenue shares in each market (MSA) in each period.

Equation (18) can be estimated via two-stage least squares (2SLS), provided we can identify valid instruments for prices. We exploit the cost side in constructing these instruments, using the total square footage of all stores operated by the firm (in all markets), the total number of stores, and the total number of employees. All three measures are proxies

[8] Recall that we have assumed that all stores operated by a single firm are a single format.

for scale which, given the prevalence of quantity discounts, is likely to have a large influence on the cost of goods sold. Since we only observe prices in a single period (but observe everything else in the model - including the instruments - in all periods), we estimate the first stage regression using only the period and firms for which we have prices. We then use the first stage estimates to construct predicted prices for all firms in all periods, and estimate (18) using a 2SLS random effects estimator.

For the supply side of our static product market, we assume that firms compete in prices. Since we have aggregated up to the level of the firm in each MSA, each supermarket can be treated as a single product firm whose profits in the static product market are given by

$$\tilde{\pi}_j\left(p, z, \xi\right) = \left(p_j - mc_j\left(q_j\right)\right) M\mathcal{S}_j\left(p, x, \xi\right) - C_j, \tag{19}$$

where we have suppressed the time subscript for brevity. $\mathcal{S}_j\left(p, z, \xi\right)$ is then the share of firm j, M is the size of the market (population)[9], and C_j is the fixed cost of production (i.e. the cost of goods sold). Assuming the existence of a pure strategy equilibrium, the price vector p must satisfy the first order conditions of profit maximization:

$$\mathcal{S}_j\left(p, z, \xi\right) + \left(p_j - mc_j\left(q_j\right)\right)\frac{\partial \mathcal{S}_j\left(p, z, \xi\right)}{\partial p_j} = 0, \tag{20}$$

or more compactly

$$p_j - mc_j = -\mathcal{S}_j / \left[\frac{\partial \mathcal{S}_j}{\partial p_j}\right].$$

Since $\frac{\partial \mathcal{S}_j}{\partial p_j} = \alpha_j \mathcal{S}_j(1 - \mathcal{S}_j)$ in the standard logit model, we can then express the gross profit margin of firm j as

$$\frac{p_j - mc_j}{p_j} = \frac{1}{\alpha_j p_j (1 - \mathcal{S}_j)}$$

and the marginal cost of firm j as

$$mc_j = p_j - \frac{1}{\alpha_j (1 - \mathcal{S}_j)}.$$

Following the standard discrete choice literature (e.g. Berry, Levinsohn, and Pakes (1995)), we assume that the natural log of marginal costs is a linear function of observed

[9]Note that there is a duplication of notation (M represents population here and the total number of markets elsewhere). This abuse of notation is simply to maintain a close connection with the standard notation used throughout the literature.

characteristics and project the recovered values of $\ln(mc_j)$ onto a vector of characteristics (w_j) via OLS

$$\ln(mc_j) = w_j\gamma + \omega_j,$$

where γ is a vector of cost-side parameters. Having recovered the full set of structural parameters characterizing static product market competition, we can then simulate the per period earned by each firm in any given market structure. In particular, given the observed number of firms, relevant firm types, individual store counts, and perceived qualities (ξ's), we can then impute marginal costs and re-solve the first order conditions (20) for equilibrium prices and quantities. Profit is then calculated from equation (19).

5 Empirical results

In this section, we report the empirical results from the three stages of estimation. The first exercise, which we call stage 0, is to recover the demand and cost parameters that characterize the static product market game. These estimates are used to construct the values of $\pi_i^P(a,x)$ that appear in the first term of the best response probability functions (10) that are used in constructing the overall likelihood (11). The second exercise, which we call step 1, is to construct estimates of the reduced form policy functions that characterize firms beliefs. These are used to construct the exit probability (nuisance parameter term) in (10) and in constructing the "weights" used in averaging over the various permutations of next period's market structure. Finally, the remaining dynamic structural parameters are estimated in step 2.

5.1 Empirical Results from Stage 0

We start by discussing the results of the demand estimation. Recall that the ultimate goal here is to recover a mapping from state vectors to per-period profits. This procedure involves a number of steps. First, we estimate the discrete choice demand system, using a "Berry inversion" to construct a standard random effects estimator. This procedure yields an estimate of the elasticity of demand which, along with shares and prices, can be used to back out an estimate of the marginal cost of production. Using these cost estimates, we are then able to construct predicted profits for all future states by solving for the static Nash

Table 3: Demand Parameters

Constant	1.64
	(.107)
Stores/Pop	5.60
	(.073)
SC Dummy	.063
	(.013)
Price	−.049
	(.001)
R^2	0.49
# Obs	18889
# Firms	1762

Standard Errors in parentheses.

equilibrium in prices.

The results of the demand estimation are presented in Table 3. The coefficients all have the expected signs and are significant at all levels. Not surprisingly, store density has a strong and positive impact on demand, as does the dummy variable indicating that the firm operates Supercenters. The coefficient on price is negative and large enough in magnitude that the every firm is pricing on the elastic portion of the demand curve. The average predicted gross margin is 30%, which is reasonably close to industry estimates (typically 26%).[10]

To evaluate the predictive quality of these estimates, we also include the results of a simple linear regression of per capita profit on the number of firms of each type (N^{SC} and N^{SM}), a firm's own store density (d_j), the average density of its competitors ($\bar{d}_{-j}$), and corresponding measures of perceived quality (ξ_j and $\bar{\xi}_{-j}$). These results, which are provided simply for illustration (since the second stage simulations solve for equilibrium profits using the first order conditions of the static maximization problem) are presented in Table 4. Again, the coefficients all have the expected signs and are significant at all levels. Specifically, profits are strongly increasing in own store density and own quality and decreasing in the average density and quality of a firm's rivals. The number of competing

[10] The industry estimates are based on an analysis of corporate filings for publicly traded firms (e.g. 10-K reports).

firms has a negative impact which is stronger for rivals of the same type.

Table 4: Profit Functions

Dependent Variable: π/pop		
	Supermarkets	Supercenters
Own Store Density (d_j)	4.84 (.186)	16.44 (1.08)
Rival's Store Density $\left(\bar{d}_{-j}\right)$	-3.42 (.421)	-2.09 (.768)
Supercenters $\left(N^{SC}\right)$	$-.166$ (.045)	$-.463$ (.103)
Supermarkets $\left(N^{SM}\right)$	$-.211$ (.021)	$-.128$ (.039)
Own Quality $\left(\xi_j\right)$	.791 (.047)	.542 (.097)
Rival's Quality $\left(\bar{\xi}_{-j}\right)$	$-.819$ (.069)	$-.319$ (.139)
Constant	1.50 (.154)	1.50 (.390)
R^2	.70	.84
Number of Observations	509	140

Standard Errors in parentheses.

5.2 Empirical Results from Step 1

This next set of empirical results are aimed at characterizing the policy functions of incumbent firms and potential entrants and are used as inputs to step 2. These policy functions are estimated as four separate regressions, broken out by firm type. The first policy function is for supermarket incumbents and is estimated using a multinomial logit. The results are presented in Table 6 the appendix. The remaining policy functions concern supercenter incumbents, supermarket entrants, and supercenter entrants. They are presented in Table 7, 8, and 9 respectively. Since these are reduced form relationships, there is no structural interpretation to the coefficient estimates, which are presented simply for completeness. The main point of the first stage is to approximate, as best as possible, the actual strategies of each firm type.

5.3 Empirical Results from Step 2

In this part of the estimation we recover the cost parameters in (13) and (14). Note that since supercenter firms do not exit or close stores, we cannot recover their full set of dynamic parameters. Therefore, we focus only on supermarkets (which are the focus of our counterfactual experiments). The results of the PML estimation are presented in Table 5. The coefficients are in millions of dollars. For example, the cost of opening a single store is estimated to be about $22.3 million, while a firm can expect to recover about $15 million when it closes a store. Note that these costs include the one-time construction costs associated with building and outfitting the store, along with any ongoing fixed costs (e.g. lease payments, labor contracts) that the firm is committed to up front. As one might expect, costs are convex in the number of stores opened, which is consistent with the fact that firms rarely open more than one store at a time. Initial build costs are similar to the costs of adding incremental stores.

Table 5: Supermarket Investment Costs

	Incumbents			Entrants	
Scrap Value	Constant	16.6 (.430)	Entry Cost	Build 1	−23.2 (.703)
	Per Store	15.5 (.252)		Build 2	−66.4 (.893)
Building Costs	Open 1	−22.3 (.233)		Build 3	−112.1 (1.12)
	Open 2	−55.0 (.467)			
	Open 3	−101.0 (.701)			
Selloff Value	Close 1	15.0 (.233)			
	Close 2	29.8 (.467)			
	Close 3	44.6 (.701)			

Standard Errors in parentheses.

6 Policy Experiments

This section describes work that is currently in progress. For now, we simply provide a road map intended to clarify the purpose of the estimators described above and their use in conducting the policy experiments that constitute the central empirical contribution of this paper.

The parameters and distributions estimated in the previous section will be used here as inputs for a series of policy experiments. In particular, we will use a discrete control version of the algorithm proposed in Pakes and McGuire (2001) (PM) to evaluate the impact of the supercenter format on competition in the supermarket industry. The fact that Wal-Mart has yet to close a store or exit entirely from an active market implies that we cannot recover the full set of structural parameters that characterize Wal-Mart's equilibrium behavior, so even though we can estimate the model with both types of firms, we cannot re-solve for the equilibrium that was played in the data without imposing further assumptions. Fortunately, our central counterfactual exercise – characterizing the change in consumer surplus associated with eliminating the supercenter format altogether – only requires re-solving the equilibrium for the players for whom we can recover the full set of structural parameters: the conventional supermarket firms. An estimate of the relevant baseline comparison (consumer welfare with supercenters) is already available in the data. Our first exercise is simply to compare the welfare estimates (and the resulting changes in market structure) from the static and dynamic models.

Because our game involves controls that are entirely discrete, it is reasonably straightforward to implement a discrete control version of the stochastic PM algorithm in our context (we are already using monte carlo integration as part of the estimation routine). This is the key to accommodating a large state space with several players and a large number of potential actions, a situation which would be intractable using the original (non-stochastic) PM algorithm.

In addition to the elimination of the supercenter format, we will also consider several other comparative dynamics aimed at characterizing the types of markets that are most/least likely to incur supercenter entry, both in terms of consumer demographics and incumbent market structures. Finally, by imposing some additional structure – namely, assuming that Wal-Mart's salvage values are proportional to those of conventional supermarkets[11] – we can consider an even richer set of counterfactual exercises. In particular, we can look at how policies that raise Wal-Mart's fixed or marginal costs would impact both consumer and producer surplus (as this involves re-solving the model with both types of firms).

A more comprehensive discussion will be added in a future version of the paper (once the code for the stochastic PM algorithm is finalized).

7 Conclusion

This paper proposes and estimates a model of dynamic competition in the supermarket industry. Using recently developed two-step estimation techniques, we recover the structural parameters governing demand, pricing decisions, incremental investment, and entry costs. We then use these parameter estimates to evaluate policies aimed at eliminating supercenters.

[11] Specifically, we will assume that Wal-Mart can recover the same percentage of their (significantly larger) initial investment as the conventional supermarket firms do.

Table 6: Policy Parameters for Supermarket Incumbents

Dependent Variable	*Exit*	*Close* 3	*Close* 2	*Close* 1	*Open* 1	*Open* 2	*Open* 3
Own Store Density (d_j)	-15.12	$-.601$	1.18	1.10	2.09	2.53	2.99
	(1.22)	(.645)	(.526)	(.256)	(.234)	(.403)	(.538)
Rival Store Density $\left(\bar{d}_{-j}\right)$	6.72	1.18	2.09	.268	-3.44	-5.05	-5.04
	(1.14)	(1.84)	(1.53)	(.752)	(.614)	(1.04)	(1.21)
Supercenters $\left(N^{SC}\right)$	.655	.547	.209	.267	$-.808$	$-.250$	$-.328$
	(.093)	(.156)	(.141)	(.064)	(.054)	(.096)	(.112)
Supermarkets $\left(N^{SM}\right)$	.177	$-.906$	$-.060$	.024	$-.137$	$-.294$	$-.323$
	(.049)	(.077)	(.068)	(.031)	(.025)	(.045)	(.052)
Own Quality $\left(\xi_j\right)$	$-.440$	$-.549$	$-.479$	$-.544$	.156	.170	.756
	(.100)	(.147)	(.128)	(.060)	(.053)	(.096)	(.125)
Rival's Quality $\left(\bar{\xi}_{-j}\right)$	.586	$-.238$	$-.066$	.397	$-.764$	-1.29	-1.16
	(.201)	(.315)	(.261)	(.123)	(.103)	(.174)	(.206)
Population Growth	-26.9	$-.281$	-38.6	-11.6	21.0	36.1	42.1
	(19.6)	(32.7)	(31.6)	(13.4)	(10.2)	(17.2)	(19.1)
Population	$-.002$	.008	.007	.005	.006	.007	.008
	(.001)	(.003)	(.001)	(.001)	(.001)	(.001)	(.001)
Constant	22.8	-4.22	34.2	8.58	-22.7	-38.4	-44.9
	(19.8)	(38.9)	(31.8)	(13.5)	(10.3)	(17.4)	(19.2)
Log Likelihood				-13174.1			
Observations				15239			

Standard errors in parentheses. Baseline alternative is "do nothing".

Table 7: Policy Parameters for Supercenter Incumbents

Dependent Variable	*Exit*	*Open* 1	*Open* 2	*Open* 3
Own Store Density (d_j)	-47.6	-1.90	-9.15	5.20
	(13.6)	(1.45)	(3.44)	(3.31)
Rival Store Density $\left(\bar{d}_{-j}\right)$	10.4	$.470$	-1.12	-1.84
	(6.00)	(1.11)	(2.12)	(2.74)
Supercenters $\left(N^{SC}\right)$	1.50	$-.668$	$-.574$	$-.668$
	(.448)	(.151)	(.263)	(.357)
Supermarkets $\left(N^{SM}\right)$	$.155$	$-.084$	$-.025$	$.096$
	(.251)	(.054)	(.095)	(.114)
Own Quality $\left(\xi_j\right)$	$.512$	$-.509$	$-.629$	-1.45
	(.731)	(.153)	(.259)	(.286)
Rival's Quality $\left(\bar{\xi}_{-j}\right)$	2.65	$-.296$	$-.322$	$-.374$
	(.956)	(.185)	(.351)	(.457)
Population Growth	62.3	3.17	37.3	85.4
	(67.7)	(22.4)	(35.1)	(43.9)
Population	$-.031$	$.006$	$.008$	$.014$
	(.017)	(.001)	(.001)	(.001)
Constant	-68.2	-3.59	-39.1	-90.0
	(69.3)	(22.6)	(35.5)	(44.1)
Log Likelihood	-1726.3			
Observations	2273			

Standard errors in parentheses. Baseline alternative is "do nothing".

Table 8: Policy Parameters for Supermarket Entrants

Dependent Variable	*Open* 1	*Open* 2	*Open* 3
Rival Store Density $\left(\bar{d}_{-j}\right)$	-8.01	3.99	-4.46
	(2.38)	(6.07)	(5.84)
Supercenters $\left(N^{SC}\right)$	$-.463$	$.260$	$-.575$
	(.159)	(.467)	(.601)
Supermarkets $\left(N^{SM}\right)$	$-.148$	$-.220$	$-.474$
	(.082)	(.259)	(.280)
Rival's Quality $\left(\bar{\xi}_{-j}\right)$	$-.553$	$.465$	-2.65
	(.331)	(.981)	(.999)
Population Growth	26.9	-77.6	13.3
	(28.3)	(111)	(118)
Population	$-.033$	$-.006$	$-.001$
	(.006)	(.007)	(.002)
Constant	-26.7	73.0	-15.9
	(28.6)	(112)	(118)
Log Likelihood		-724.2	
Observations		3312	

SEs in parentheses. Baseline alternative is "do not enter".

Table 9: Policy Parameters for Supercenter Entrants

Dependent Variable	*Open* 1	*Open* 2
Rival Store Density $\left(\bar{d}_{-j}\right)$	-4.30 (1.78)	$-.856$ (.554)
Supercenters $\left(N^{SC}\right)$	-1.98 (.191)	-2.55 (.442)
Supermarkets $\left(N^{SM}\right)$	$-.210$ (.073)	$-.502$ (.152)
Rival's Quality $\left(\bar{\xi}_{-j}\right)$	-1.03 (.284)	.856 (.554)
Population Growth	-65.6 (29.3)	-13.5 (49.6)
Population	$-.005$ (.001)	$-.002$ (.001)
Constant	66.1 (29.5)	13.7 (49.9)
Log Likelihood	-841.2	
Observations	3312	

SEs in parentheses. Baseline alternative is "do not enter".

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