Supermarket Pricing Strategies*

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Abstract

Most supermarket firms choose to position themselves by offering either "Every Day Low Prices" (EDLP) across several items or offering temporary price reductions (promotions) on a limited range of items. While this choice has been addressed from a theoretical perspective in both the marketing and economic literature, relatively little is known about how these decisions are made in practice, especially within a competitive environment. This paper exploits a unique store level dataset consisting of every supermarket operating in the United States in 1998. For each of these stores, we observe the pricing strategy the firm has chosen to follow, as reported by the firm itself. Using a system of simultaneous discrete choice models, we estimate each store's choice of pricing strategy as a discrete game of incomplete information. In contrast to the predictions of the theoretical literature, we find strong evidence that firms cluster by strategy by choosing actions that agree with those of its rivals. We also find a significant impact of various demographic and store/chain characteristics, providing some qualified support for several specific predictions from marketing theory.

Keywords: EDLP, promotional pricing, positioning strategies, supermarkets, discrete games.

JEL Classification Codes: M31, L11, L81

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1 Introduction

While firms compete along many dimensions, pricing strategy is clearly one of the most important. In many retail industries, pricing strategy can be characterized as a choice between offering relatively stable prices across a wide range of products (often called "every day low pricing") or emphasizing deep and frequent discounts on a smaller set of goods (referred to as "promotional" or PROMO pricing). Although Wal-Mart did not invent the concept of every day low pricing (EDLP), the successful use of EDLP was a primary factor in their rapid rise to the top of the Fortune 500, spawning a legion of followers selling everything from toys (Toys R Us) to building supplies (Home Depot). In the 1980s, it appeared that the success and rapid diffusion of the EDLP strategy could spell the end of promotions throughout much of retail. However, by the late 1990s, the penetration of EDLP had slowed, leaving a healthy mix of firms following both strategies, and several others who used a mixture of the two.

Not surprisingly, pricing strategy has proven to be a fruitful area of research for marketers. Marketing scientists have provided both theoretical predictions and empirical evidence concerning the types of consumers that different pricing policies are likely to attract (e.g. Lal and Rao, 1997; Bell and Lattin, 1998). While we now know quite a bit about where a person is likely to shop, we know relatively little about how pricing strategies are chosen by retailers. There are two primary reasons for this. First, these decisions are quite complex: managers must balance the preferences of their customers and their firm's own capabilities against the expected actions of their rivals. Empirically modeling these actions (and reactions) requires formulating and then estimating a complex discrete game, an exercise which has only recently become computationally feasible. The second is the lack of appropriate data. While scanner data sets have proven useful for analyzing consumer behavior, they typically lack the breadth necessary for tackling the complex mechanics of inter-store competition.[1] The goal of this paper is to combine newly developed methods for estimating static games with a rich, nation-wide dataset on store level pricing policies to identify the primary factors that drive pricing behavior in the supermarket industry.

Exploiting the game theoretic structure of our approach, we aim to answer three ques-

[1] Typical scanner data usually reflect decisions made by only a few stores in a limited number of markets.

tions that have not been fully addressed in the existing literature. First, to what extent do supermarket chains tailor their pricing strategies to local market conditions? Second, do certain types of chains or stores have advantages when it comes to particular pricing strategies? Finally, how do firms react to the expected actions of their rivals? We address each of these questions in detail.

The first question naturally invites a market "pull" driven explanation in which consumer demographics play a key role in determining which pricing strategy firms choose. In answering this question, we also aim to provide additional empirical evidence that will inform the growing theoretical literature on pricing related games. Since we are able to assess the impact of local demographics at a much broader level than previous studies, our results provide more conclusive evidence regarding their empirical relevance.

The second question posed above addresses the match between a firm's strategy and its chain-specific capabilities. In particular, we examine whether particular pricing strategies (e.g. EDLP) are more profitable when firms make complementary investments (e.g. larger stores and more sophisticated distribution systems). The empirical evidence on this matter is scarce - this is the first paper to address this issue on a broad scale. Furthermore, because our dataset includes every existing supermarket, we are able to exploit variation both within and across chains to assess the impact of store and chain level differences on the choice of pricing strategy.

Finally, we address the role of competition posed in our third question by analyzing firms' reactions to the expected choices of their rivals. In particular, we ask whether firms face incentives to distinguish themselves from their competitors (as in most models of product differentiation) or instead face pressures to conform (as in network or switching cost models)? This question is the primary focus of our paper and the feature that most distinguishes it from earlier work.

Our results shed light on all three questions. First, we find that consumer demographics play a significant role in the choice of local pricing strategies: firms choose the policy that their consumers demand. Furthermore, the impact of these demographic factors is consistent with both the existing marketing literature and conventional wisdom. For example, EDLP is favored in low income, racially diverse markets, while PROMO clearly targets the rich. However, a key implication of our analysis is that these demographic factors act as a coordinating device for rival firms, helping shape the pricing landscape by defining an equilibrium correspondence. Second, we find that complementary investments are key: larger stores and vertically integrated chains are significantly more likely to adopt EDLP. Finally, and most surprisingly, we find that stores competing in a given market have incentives to coordinate their actions. Rather than choosing a strategy that distinguishes them from their rivals, stores choose strategies that match. This finding is in direct contrast to existing theoretical models that view pricing strategy as a form of differentiation. While we do not aim to test a particular theory of strategic pricing behavior, we hope a deeper examination of these competitive interactions will address important issues that have remained unanswered.

Our paper makes both substantive and methodological contributions to the marketing literature. On the substantive front, our results offer an in-depth look at the supermarket industry's pricing practices, delineating the role of three key factors (demand, supply and competition) on the choice of pricing strategy. We provide novel, producer-side empirical evidence that complements various consumer-side models of pricing strategy. In particular, we find qualified support for several claims from the literature on pricing demographics, including Bell and Lattin's (1998) model of basket size and Lal and Rao's (1997) positioning framework, while at the same time highlighting the advantages of chain level investment. Our focus on competition also provides a structural complement to Shankar and Bolton's (2004) descriptive study of price variation in supermarket scanner data, which emphasized the role of rival actions. Our most significant contribution, however, relates to the finding that stores in a particular market do not use pricing strategy as a differentiation device but instead coordinate their actions. This result provides a direct challenge to the conventional view of retail competition, opening up new and intriguing avenues for future theoretical research. Our econometric implementation also contributes to the growing literature in marketing and economics on the estimation of static discrete games, as well as the growing literature on peer effects [2]. In particular, our incorporation of multiple sources of private

[2]Recent applications of static games include technology adoption by internet service providers (Augereau et al. 2006), product variety in retail eyewear (Watson, 2005), location of ATM branches (Gowrisankaran and Krainer, 2004), and spatial differentiation among supermarkets (Orhun, 2005), discount stores (Zhu et al., 2005), and video stores (Seim, 2006). Structural estimation of peer effects is the focus of papers by Brock and Durlauf (2002), Bayer and Timmins (2006), and Bajari et al. (2005).

information and our construction of competitive beliefs are novel additions to these emerging literatures.

The rest of the paper is organized as follows. Section 2 provides an overview of the pricing landscape, illustrating the importance of local factors in determining store level strategies. Section 3 introduces our formal model of pricing strategy and briefly outlines our estimation method and identification strategy. Section 4 describes the dataset. Section 5 provides the details of how we implement the model, including the construction of distinct geographic markets, the selection of covariates, and our two-step estimation strategy. Section 6 provides our main empirical results and discusses their implications. Section 7 concludes with directions for future research.

2 The Supermarket Pricing Landscape

Supermarket firms compete along many dimensions, enticing customers with an attractive mix of products, competitive prices, convenient locations, and a host of other services, features, and marketing programs. In equilibrium, firms choose the bundle of services and features that maximize profits, conditional on the types of consumers they expect to serve and their beliefs regarding the actions of their rivals. Building a formal model of a chain's overall positioning strategy is an intractably complex problem, involving an extremely high dimensional multiple discrete/continuous choice problem that is well beyond the current frontier. Our focus is more modest, emphasizing only a single aspect of a firms positioning strategy: their pricing policy. The vast majority of both marketers and practitioners frame the pricing decision as choice between offering "every day low prices" across a wide category of products or deep but temporary discounts on only a few, labeling the first strategy EDLP and the second Hi-Lo or PROMO. This is, of course, a simplification. Actual pricing decisions are made in conjunction with an overall positioning strategy and tailored to particular operational advantages. For example, successful implementation of EDLP typically involves offering a deeper and narrower product line than PROMO, allowing these firms to leverage greater scale economies (in particular categories), reduce their inventory carrying costs, and lower their advertising expenses. On the other hand, PROMO pricing gives firms greater flexibility in clearing overstock, allows them to quickly capitalize on deep manufacturer discounts, and facilitates the use of consumer loyalty programs (e.g. frequent shopper cards). Given the information in our dataset, we have chosen to focus squarely on the pricing dimension, although we will account for some of the operational motives by conditioning on observable features of each chain.

Even abstracting from an overall positioning strategy, the EDLP-PROMO dichotomy is too narrow to adequately capture the full range of firm behavior. In practice, firms can choose a mixture of EDLP and PROMO, varying either the *number* of categories they put on sale or changing the *frequency* of sales across some or all categories of products. Not surprisingly, practitioners have coined a term for these practices, hybrid pricing. What constitutes HYBRID pricing is necessarily subjective, depending on an individual's own beliefs regarding how much price variation constitutes a departure from "pure" EDLP. Both the data and definitions used in this paper are based on a specific store level survey conducted by Trade Dimensions in 1998, which asked individual store managers to choose which of the following categories best described their store's pricing policy

- **Everyday Low Price (EDLP):** Little reliance on promotional pricing strategies such as temporary price cuts. Prices are consistently low across the board, throughout all packaged food departments.
- **Promotional (Hi-Lo) Pricing:** Heavy use of specials, usually through manufacturer price breaks or special deals.
- **Hybrid EDLP/Hi-Lo:** Combination of EDLP and Hi-Lo pricing strategies.

According to Trade Dimensions, the survey was designed to allow for a broad interpretation of the HYBRID strategy, as they wanted it to capture deviations along either the temporal (i.e. number of sales per year) or category based dimensions (i.e. number of categories on deal). Since the survey was of store managers but administered by brokers (who explained the questions), it was ultimately up to both of them to decide the best fit. We believe that pricing strategy is best viewed as a continuum, with pure EDLP (i.e. constant margins across all categories) on one end and pure PROMO (i.e. frequent sales on all categories) at the other. This dataset represents a coarse discretization of that continuum.

Without this data on individual stores, it is tempting to conclude that all pricing strategies are determined at the level of the chain. To examine the issue more closely, we focus in on a single chain in a single market: the Pathmark chain in New Jersey. Figure 1 shows the spatial locations of every Pathmark store in New Jersey, along with its pricing strategy. Two features of the data are worth emphasizing. We address them in sequence.

First, Pathmark does not follow a single strategy across its stores: 42% of the stores use PROMO pricing, 33% follow EDLP, and the remaining 25% use HYBRID. The heterogeneity in pricing strategy observed in the Pathmark case is not specific to this particular chain. Table 3 shows the store level strategies chosen by the top 15 U.S. supermarkets (by total volume) along with their total store counts. As with Pathmark, the major chains are also surprisingly heterogeneous. While some firms appear to have a clear focus (e.g. Wal-Mart, H.E. Butt, Stop & Shop), others are more evenly split (e.g. Lucky, Cub Foods). This pattern extends to the full set of firms. Table 4 shows the pricing strategies chosen by large and small chains, using four alternative definitions of "large" and "small".[3] While "large" chains seem evenly distributed across the strategies and "small" chains seem to favor PROMO, firm size is not the primary determinant of pricing strategy.

The second noteworthy feature of the Pathmark data is that even geographically proximate stores adopt quite different pricing strategies. While there is some clustering at the broader spatial level (north vs. south New Jersey), the extent to which these strategies are interlaced is striking. Again, looking beyond Pathmark and New Jersey confirms that this within-chain spatial heterogeneity is not unique to this particular example. Broadly speaking, the data reveal only a weak relationship between geography and pricing strategy. While southern chains such as Food Lion are widely perceived to favor EDLP and Northeastern chains like Stop & Shop are thought to prefer promotional (PROMO) pricing, regional variation does not capture the full story. Table 2 shows the percent of stores that choose either EDLP, HYBRID, or PROMO pricing in eight geographic regions of the U.S. While PROMO pricing is most popular in the Northeast, Great Lakes and central Southern regions, it is far from dominant, as both the EDLP and HYBRID strategies enjoy healthy

[3] The four definitions of firm size are: chain/independent, vertically integrated and not, large/small store, and many/few checkouts. A chain is defined as having 11 or more stores, while an independent has 10 of fewer. Vertically integrated means the firm operates its own distribution centers. Large versus small store size and many versus few checkouts are defined by the upper and lower quartiles of the full store level census.

shares there as well. EDLP is certainly popular in the South and Southeast, but PROMO still draws double digit shares in both regions. This heterogeneity in pricing strategy is easily illustrated using the spatial structure of our dataset. Figure 2 plots the geographic location of every store in the U.S., along with their pricing strategy. As is clear from the panels corresponding to each pricing strategy, there is no obvious pattern at this level of aggregation. Taken together, these observations suggest looking elsewhere for the primary determinants of pricing strategy. We turn next to the role of market demographics and then to the nature and degree of competition.

Table 5 contains the average demographic characteristics of markets served by stores of each type. PROMO pricing is associated with smaller households, higher income, fewer automobiles per capita, and less racial diversity, providing some support for Bell and Lattin's (1998) influential model of "basket size"[4]. However, the differences are not overwhelming and, in many cases, statistically insignificant. We note that this does not imply that demographics are irrelevant, but rather that the aggregate level patterns linking pricing strategy and demographics are not overwhelming. We will demonstrate below that local variation in demographics helps explain why chains tend to adopt heterogeneous pricing strategies across stores.

The final row of Table 5 contains the share of rival stores in the competing market that employ the same strategy as the store being analyzed. Here we find a strong result: 50% of a store's rivals in a given location employ the same pricing strategy as the store being analyzed. Competitor factors were also the most important explanatory factor in Shankar and Bolton's (2004) analysis of pricing variability in supermarket scanner data. In particular, they note that "what is most striking, however, is that the competitor factors are the most dominant determinants of retailer pricing in a broad framework that included several other factors". Even at this rather coarse level of analysis, the data reveal that most stores choose similar pricing strategies. This pattern clearly warrants a more detailed investigation and is the focus of our structural model.

[4] Bell and Lattin (1998) find that the most important features of shopping behavior can be captured by two interrelated choices: basket size (how much you buy) and shopping frequency (how often you go). They suggest that large or fixed basket shoppers (i.e. those who buy more and shop less) will more sensitive to the overall basket price than those who shop frequently and will therefore prefer EDLP pricing to PROMO. They present empirical evidence that is consistent with this prediction.

Three central features of supermarket pricing strategy emerge from this discussion. First, supermarket chains adopt heterogeneous pricing strategies, suggesting that demand related forces may outweigh any advantages accruing from chain level specialization. Second, local market factors play a key role in shaping demand characteristics. Finally, any empirical analysis of pricing strategy must include the role of competition. While investigating the role of market demographics and firm characteristics is not conceptually difficult, quantifying the structural impact of rival pricing strategies on firm behavior requires a formal game theoretic model of pricing behavior that accounts for the simultaneity of choices. In the following section, we embed pricing strategy in a discrete game that accommodates both local demographics and the strategies of rival firms. We then estimate this model using a two-step approach developed by Bajari et al. (2005).

3 Theoretical Framework

A supermarket's choice of pricing strategy is naturally framed as a discrete game between a finite set of players. Each firm's optimal choice is determined by the underlying market conditions, its own characteristics and individual strengths, and its expectations regarding the actions of its rivals. Notably, the strategic choice of each firm is a function of the anticipated choices of its competitors, and vice versa. If strategic expectations were ignored, a firm's choice of pricing strategy would be a straightforward discrete choice problem. However, since firms will condition their strategies on their beliefs regarding rivals' actions, this discrete choice must be modeled using a system of simultaneous equations. In what follows, we outline our model in detail.

3.1 A Strategic Model of Supermarket Pricing

In our framework, firms (i.e. supermarket chains[5]) make a discrete choice of pricing strategy, selecting among three alternatives: everyday low pricing, promotional pricing, and a hybrid strategy. While there is clearly a role for dynamics in determining an optimal pricing policy, we assume that firms act simultaneously in a static environment, taking entry decisions as

[5]Henceforth, we will use "chains" and "firms" interchangeably.

given.[6] A static treatment of competition is not altogether unrealistic since these pricing investments involve substantial investments in communication and positioning related costs that are not easily reversible.[7]

In what follows, we assume that competition takes place in 'local' markets,[8] each contained in a 'global' market (here, an MSA). Before proceeding further, we must introduce some additional notation. Stores belonging to a given chain $c = 1, .., C$, that are located in a local market $l_m = 1, .., L_m$, in an MSA $m = 1, .., M$, will be indexed using $i_c^{l_m} = 1, .., N_c^{l_m}$. The total number of stores in a particular chain in a given MSA is $N_c^m = \sum_{l_m=1}^{L_m} N_c^{l_m}$, while the total number of stores in that chain across all MSAs is $N_c = \sum_{m=1}^{M} N_c^m$. In each local market, chains select a pricing strategy (action) a from the three element set $K = \{E, H, P\}$, where $E \equiv EDLP$, $H \equiv HYBRID$, and $P \equiv PROMO$. If we observe a market l_m containing $N^{l_m} = \sum_{c=1}^{C} N_c^{l_m}$ players for example, the vector of possible action profiles is then $A_{l_m} = \{E, H, P\}^{N_c^{l_m}}$ with generic element $a_{l_m} = (a_1, a_2, ..., a_{i_c^{l_m}}, ..., a_{N_c^{l_m}})$. The vector of actions of $i_c^{l_m}$'s competitors is denoted $a_{-i_c^{l_m}} = (a_1, .., a_{i_c^{l_m}-1}, a_{i_c^{l_m}+1}, ..a_{N_c^{l_m}})$.

In a given market, a particular chain's state vector is denoted $s_c^m \in S_c^m$, while the state vector for the market as a whole is $s^m = (s_1^m, ..., s_{N_c}^m) \in \prod_{c=1}^{N_c^m} S_c^m$. The state vector s^m is known to all firms and observed by the econometrician. It describes features of the market and characteristics of the firms that are assumed to be determined exogenously. For each firm, there are also three *unobserved* state variables (corresponding to the three

[6] Ideally, entry and pricing decisions would be modeled jointly, allowing for firms that favor EDLP, for example, to prefer certain types of markets. Unfortunately, even modeling supermarket location choice alone would be intractable, as it would require estimating a coordinated choice of up to 1200 store locations by each of hundreds of firms (the current state of the art (Jia, 2006) can handle two firms). Nonetheless, we believe that ignoring entry will not yield significant bias in our setting, since logistical issues far outweigh pricing strategy in determining entry decisions. In particular, supermarket chains choose store locations to maximize supply side density economies, designing hub and spoke networks to minimize transportation costs. The spatial distribution of stores tracks population very closely; the gaps that one would expect if firms were cherry picking pricing-friendly markets simply do not exist. Ellickson (2006) presents empirical evidence consistent with these claims.

[7] Since this is not an entry game (and pricing decisions are relatively sunk), we are not particularly concerned about the possibility of ex post regret that can sometimes occur in static games (Einav, 2003).

[8] In our application, a local market is a small geographic trading area, roughly the size of a zip code. The procedure we used to construct these markets is described in Section 5.2.

pricing strategies) that are treated as private information of the firm. These unobserved state variables are denoted $\epsilon_{i_c^{l_m}}\left(a_{i_c^{l_m}}\right)$, or more compactly $\epsilon_{i_c^{l_m}}$, and represent firm specific shocks to the profitability of each strategy. The private information assumption makes this a game of incomplete or asymmetric information (e.g. Harsanyi, 1973) and the appropriate equilibrium concept one of Bayesian Nash Equilibrium (BNE).[9] For any given market, the $\epsilon_{i_c^{l_m}}$'s are assumed to be *iid* across firms and actions, and drawn from a distribution $f\left(\epsilon_{i_c^{l_m}}\right)$ that is known to everyone, including the econometrician.

Firms choose pricing strategies in each store independently, with the objective of maximizing expected profits in each store. In market l_m, the profit earned by store i_c is given by

$$\pi_{i_c^{l_m}} = \Pi_{i_c^{l_m}}\left(s^m, a_{i_c^{l_m}}, a_{-i_c^{l_m}}\right) + \epsilon_{i_c^{l_m}} \tag{1}$$

where $\Pi_{i_c^{l_m}}$ is a known and deterministic function of states and actions (both own and rival's). This extends the standard discrete choice framework by allowing the actions of a firm's rivals to enter its payoff function. Since the ϵ are treated as private information, a firm's decision rule $a_{i_c^{l_m}} = d_{i_c^{l_m}}\left(s^m, \epsilon_{i_c^{l_m}}\right)$ is a function of the common state vector and its own ϵ, but *not* the private information of its rivals. The probability that a given firm chooses action k conditional on the common state vector is then given by

$$P_{i_c^{l_m}}\left(a_{i_c^{l_m}} = k\right) = \int 1\left\{d_{i_c^{l_m}}\left(s^m, \epsilon_{i_c^{l_m}}\right) = k\right\} f\left(\epsilon_{i_c^{l_m}}\right) d\epsilon_{i_c^{l_m}}, \tag{2}$$

where $1\left\{d_{i_c^{l_m}}\left(s, \epsilon_{i_c^{l_m}}\right) = k\right\}$ is an indicator function equal to 1 if store $i_c^{l_m}$ chooses action k and 0 otherwise. These probabilities represent the expected actions of a given store from the perspective of the other stores in the market. We let $\mathbf{P}_{l_m}$ denote the set of these probabilities for a given local market. Since the firm does not observe the actions of its competitors prior to choosing an action, it makes decisions based on these expectations. The expected profit for firm $i_c^{l_m}$ from choosing action $a_{i_c^{l_m}}$ is then

$$\begin{aligned}
\widetilde{\pi}_{i_c^{l_m}}\left(a_{i_c^{l_m}}, s^m, \epsilon_i, \mathbf{P}_{l_m}\right) &= \widetilde{\pi}_{i_c^{l_m}}\left(a_{i_c^{l_m}}, s^m\right) + \epsilon_{i_c^{l_m}} && (3)\\
&= \sum_{a_{-i_c^{l_m}}} \Pi_{i_c^{l_m}}\left(s^m, a_{i_c^{l_m}}, a_{-i_c^{l_m}}\right) P_{-i_c^{l_m}} + \epsilon_{i_c^{l_m}} && (4)
\end{aligned}$$

[9] Treating the types as private information greatly simplifies the computational burden of estimation. By avoiding the complicated regions of integration that arise in the complete information case, we can accommodate a much larger number of players and potential actions.

where $P_{-i_c^{l_m}} = \prod_{j \neq i_c^{l_m}} P_j \left(a_j | s^m\right)$. Given these expected profits, the optimal action for a store is given by

$$\Psi_{i_c^{l_m}} = \Pr \left\{ \epsilon_{i_c^{l_m}} | \widetilde{\pi}_{i_c^{l_m}} \left(a_{i_c^{l_m}}, s^m \right) + \epsilon_{i_c^{l_m}} \left(a_{i_c^{l_m}} \right) > \widetilde{\pi}_{i_c^{l_m}} \left(a'_{i_c^{l_m}}, s^m \right) + \epsilon_{i_c^{l_m}} \left(a'_{i_c^{l_m}} \right) \ \forall \ a'_{i_c^{l_m}} \neq a_{i_c^{l_m}} \right\}. \tag{5}$$

If the ϵ_i's are drawn from a Type I Extreme Value distribution (i.e. Gumbel errors), the Bayesian Nash Equilibrium to this static game must satisfy a system of logit equations (i.e. best response functions). Because a firm's optimal action is unique by construction, there is no need to consider mixed strategies. The general framework described above has been applied in several economic settings and its properties are well understood. In particular, existence of equilibrium follows easily from Brouwer's fixed point theorem (McKelvy and Palfrey, 1995).

To proceed further, we need to choose a particular specification for the expected profit functions. We will assume that the profit that accrues to store $i_c^{l_m}$ from choosing strategy k in location l_m is given by

$$\widetilde{\pi}_{i_c^{l_m}} \left(a_{i_c^{l_m}} = k, s^m, \epsilon_i, \mathbf{P}_{l_m} \right) = s^{m\prime} \beta_k + \rho^E_{-i_c^{l_m}} \alpha_{k1} + \rho^P_{-i_c^{l_m}} \alpha_{k2} + \xi_c^m (k) + \zeta_c (k) + \varepsilon_{i_c^{l_m}} (k). \tag{6}$$

where, as before, s^m is the common state vector of both market (local and MSA) and firm characteristics (chain and store level). The $\rho^E_{-i_c^{l_m}}$ and $\rho^P_{-i_c^{l_m}}$ terms represent the expected proportion of a store's competitors in market l_m that will choose EDLP and PROMO strategies respectively:

$$\rho^{(k)}_{-i_c^{l_m}} = \frac{1}{N^{l_m}} \sum_{j \neq i_c^{l_m}} P_j \left(a_j = k\right)$$

Note that we have assumed that payoffs are a linear function of the share of stores that choose EDLP and PROMO, which simplifies the estimation problem and eliminates the need to consider the share who choose HYBRID (H). We further normalize the average profit from the PROMO strategy to zero, one of three assumptions required for identification. We discuss our identification strategy in detail in section 5.6. In addition, we have assumed that the private information available to store $i_c^{l_m}$ (i.e. $\epsilon_{i_c^{l_m}}$) can be decomposed into three additive stochastic components:

$$\epsilon_{i_c^{l_m}} (k) = \xi_c^m (k) + \zeta_c (k) + \varepsilon_{i_c^{l_m}} (k). \tag{7}$$

where $\varepsilon_{i_c^{l_m}}(k)$ represents local market level private information, $\xi_c^m(k)$ is the private information that a chain possesses about a particular global market (MSA), and $\zeta_c(k)$ is a non-spatial component of private information that is chain specific. Following our earlier discussion, we will assume that $\varepsilon_{i_c^{l_m}}(k)$ is an *i.i.d.* Gumbel error. We further assume that the other components are jointly distributed with distribution function $F(\xi_c^m(k), \zeta_c(k); \Omega)$, where Ω is a set of parameters associated with F. Denoting the parameter vector $\Theta = \{\beta, \alpha, \Omega\}$ and letting $\delta_{i_c^{l_m}}(k)$ be an indicator function such that

$$\delta_{i_c^{l_m}}(k) = \begin{cases} 1 & \text{if } a_{i_c^{l_m}} = k \\ 0 & \text{if } a_{i_c^{l_m}} \neq k \end{cases} \tag{8}$$

the optimal choice probabilities for a given store can be written as

$$\Psi_{i_c^{l_m}}\left(a_{i_c^{l_m}} = k | \boldsymbol{\Theta}, \mathbf{P}_{l_m}, \mathbf{X}, \xi_{l_m}(k)\right) = \frac{\exp\left(s^{m\prime}\beta_k + \rho^E_{-i_c^{l_m}}\alpha_{k1} + \rho^P_{-i_c^{l_m}}\alpha_{k2} + \xi_c^m(k) + \zeta_c(k)\right)}{\sum\limits_{k \in \{E,H,P\}} \exp\left(s^{m\prime}\beta_k + \rho^E_{-i_c^{l_m}}\alpha_{k1} + \rho^P_{-i_c^{l_m}}\alpha_{k2} + \xi_c^m(k) + \zeta_c(k)\right)} \tag{9}$$

while the likelihood can be constructed as

$$\prod_{m \in M} \int_{\zeta_c(k)} \prod_{c \in C} \int_{\xi_c^m(k)} \left\{ \prod_{l_m \in L_m} \prod_{i_c^{l_m} \in N_c^{l_m}} \left[\Psi_{i_c^{l_m}}\left(a_{i_c^{l_m}} = k | \boldsymbol{\Theta}, \mathbf{P}_{l_m}, \mathbf{s}, \xi_c^m(k), \zeta_c(k)\right)\right]^{\delta_{i_c^{l_m}}(k)} \right\} dF(\xi_c^m(k), \zeta_c(k); \Omega)$$

$$s.t.\ \mathbf{P}_{l_m} = \boldsymbol{\Psi}_{l_m}(\boldsymbol{\Theta}, \mathbf{P}_{l_m}, \mathbf{s}, \xi_c^m(k), \zeta_c(k)) \tag{10}$$

Note that the construction of the likelihood involves a system of discrete choice equations that must satisfy a fixed point constraint $(\mathbf{P}_{l_m} = \boldsymbol{\Psi}_{l_m})$. There are two main approaches for dealing with the recursive structure of this system; both are based on methods originally applied to dynamic discrete choice problems. The first, based on Rust's (1987) Nested Fixed Point (NFXP) algorithm, involves solving for the fixed point of the system at every candidate parameter vector and then using these fixed point probabilities to evaluate the likelihood. This is the method used by Seim (2006) in her analysis of the video rental market. The NFXP approach, however, is both computationally demanding and straightforward to apply only when the equilibrium of the system is unique.[10] An alternate approach, based on Hotz and Miller's (1993) Conditional Choice Probability (CCP) estimator, involves using a two-step approach that is both computationally light and more robust to multiplicity.[11] The first step of this procedure involves obtaining consistent estimates of each firm's beliefs regarding the strategic actions of its rivals. These "expectations" are then used in a second stage optimization procedure to obtain the structural parameters of interest. Given the complexity of our problem, we chose to adopt a two-step approach based on Bajari et al. (2005), who were the first to apply these methods to static games.

4 Dataset

The data for the supermarket industry are drawn from Trade Dimension's 1998 *Supermarkets Plus Database*, while corresponding consumer demographics are taken from the decennial Census of the United States. Descriptive statistics are presented in Table 1. 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.[12]

Information on pricing strategy, average weekly volume, store size, number of checkouts,

[10] It is relatively simple to construct the likelihood function when there is a unique equilibrium, although solving for the fixed point at each iteration can be computationally taxing. However, constructing a *proper* likelihood (for the NFXP) is generally intractable in the event of multiplicity, since it involves *both* solving for all the equilibria and specifying an appropriate selection mechanism. Simply using the first equilibrium you find will result in mispecification. A version of the NFXP that is robust to multiplicity has yet to be developed.

[11] Orignally developed for dynamic discrete choice problems, two-step estimators have been applied to dynamic discrete games by Aguirregabiria and Mira (2006), Bajari et al. (2006), Pakes, Ostrovsky and Berry (2002), and Pesendorfer and Schmidt-Dengler (2002). Instead of requiring a unique equilibrium to the whole game, two-step estimators simply require a unique equilibrium be played in the data. Futhermore, if the data can be partioned into distinct markets with sufficient observations (as is the case in our application), this requirement can be weakened even further.

[12] Firms in this segment operate very small stores and compete only with the smallest supermarkets (Ellickson (2006), Smith (2005)).

and additional store and chain level characteristics was gathered using a survey of each store manager, conducted by their principal food broker.[13] With regard to pricing strategy, managers are asked to choose the strategy that is closest to what their store practices on a general basis: either EDLP, PROMO or HYBRID. The HYBRID strategy is included to account for the fact that many practitioners and marketing theorists view the spectrum of pricing strategies as more a continuum than a simple EDLP-PROMO dichotomy (Shankar and Bolton, 2004). The fact that just over a third of the respondents chose the HYBRID option is consistent with this perception.

5 Empirical Implementation

The empirical implementation of our framework requires three primary inputs. First, we need to choose an appropriate set of state variables. These will be the market, store and chain characteristics that are most relevant to pricing strategy. To determine which specific variables to include, we draw heavily on the existing marketing literature. Second, we will need to define what we mean by a "market". Finally, we need to estimate beliefs and construct the empirical likelihood. We outline each of these steps in the following subsections.

5.1 Determinants of Pricing Strategy

The focus of this paper is the impact of rival pricing policies on a firm's own pricing strategy. However, there are clearly many other factors that influence pricing behavior. Researchers in both marketing and economics have identified several, including consumer demographics, rival pricing behavior, and market, chain, and store characteristics (Shankar and Bolton, 2004). Since we have already discussed the role of rival firms, we now focus on the additional determinants of pricing strategy.

Several marketing papers highlight the impact of demographics on pricing strategy (Ortmeyer et al., 1991; Hoch et al.,1994; Lal and Rao, 1997; Bell and Lattin, 1998). Of particular

[13] It should be noted that all of these variables, including the information on pricing strategy, are self-reported. However, it is extremely unlikely that the results reported below could be the product of systematic reporting error, as this would require coordination between tens of thousands of managers and thousands of brokers to willfully mis-report their practices (for no obvious personal gain).

importance are consumer factors such as income, family size, age, and access to automobiles. In most strategic pricing models, the PROMO strategy is motivated by some form of spatial or temporal price discrimination. In the spatial models (e.g. Lal and Rao, 1997; Varian, 1980), PROMO pricing is geared toward consumers who are either willing or able to visit more than one store (i.e. those with low travel costs) or, more generally, those who are more informed about price levels. The EDLP strategy instead targets those with higher travel costs or those who are less informed (perhaps due to heterogeneity in the cost of acquiring price information). In the case of temporal discrimination (Bell and Lattin, 1998; Bliss, 1988), PROMO pricing targets the customers who are willing to either delay purchase or stockpile products, while EDLP targets customers that prefer to purchase their entire basket in a single trip or at a single store. Clearly, the ability to substitute over time or across stores will depend on consumer characteristics. To account for these factors, we include measures of family size, household income, median vehicle ownership, and racial composition in our empirical analysis.

Since alternative pricing strategies will require differing levels of fixed investment (Lattin and Ortmeyer, 1991), it is important to control for both store and chain level characteristics. For example, large and small chains may differ in their ability to implement pricing strategies (Dhar and Hoch, 1997). Store level factors are also likely to play a role (Messinger and Narasimhan, 1997). For example, EDLP stores may need to carry a larger inventory and PROMO stores might need to advertise more heavily. Therefore, we include a measure of store size and an indicator variable for whether it is part of a vertically integrated chain. Finally, since the effectiveness of pricing strategies might vary by market size (e.g. urban versus rural), we include measures of geographic size, population density, and average expenditures on food.

5.2 Market Definition

The supermarket industry is composed of a large number of firms operating anywhere from 1 to 1200 outlets. We focus on the choice of pricing strategy at an individual store, abstracting away from the more complex issue of how decisions are made at the level of the chain. Since we intend to focus on store level competition, we need a suitable definition of the local market. This requires identifying the primary trade area from which each store draws potential customers. Without disaggregate, consumer-level information, the task of defining local markets requires some simplifying assumptions. In particular, we assume markets can be defined by spatial proximity alone, which can be a strong assumption in some circumstances (Bell, Ho, and Tang (1998)). However, without consumer level purchase information we can't relax this assumption. Therefore, we will try to be as flexible as possible in defining spatial markets.

Although there are many ways to group firms using existing geographic boundaries (e.g. ZipCodes or Counties), these pre-specified regions all share the same drawback: they increase dramatically in size from east to west, reflecting established patterns of population density.[14] Rather than imposing this structure exogenously, we allow the data to sort itself by using cluster analysis. In particular, we assume that a market is a contiguous geographic area, measurable by geodesic distance and containing a set of competing stores. Intuitively, markets are groups of stores that are located "close to one another". To construct these markets, we used a statistical clustering method (*K-means*) based on latitude, longitude and ZipCode information.[15] Our clustering approach produced a large set of distinct clusters that we believe to be a good approximation of the actual markets in which supermarkets compete. These store clusters are somewhat larger than a typical ZipCode, but significantly smaller than the average county.

We varied the number of clusters and found that about eight thousand best captures the retail supermarket landscape. A typical county and the clusters within it are depicted in Figure 3. As is evident from the map, our clustering method appears to capture geographic proximity in a sensible manner. While there are undoubtedly other factors (such as highways or rivers) that might cause consumers to perceive markets in slightly different ways, we believe that these geographic clusters constitute a reasonable choice of market definition for this industry. As robustness checks, we experimented with both broader and narrower definitions of the market (e.g. ZipCodes and MSAs) and found qualitatively similar results (see Appendix A.1).

[14] One exception is Census block groups, which are about half the size of a typical ZipCode. However, we feel that these areas are too small to constitute reasonably distinct supermarket trading areas.

[15] ZipCodes are required to ensure contiguity: without ZipCode information, stores in Manhattan would be included in the same market as stores in New Jersey.

5.3 Estimation Strategy

As noted above, the system of discrete choice equations presents a challenge for estimation. We adopt a two stage approach based on Bajari et al. (2005) that avoids solving for a fixed point. The first step involves obtaining a consistent estimate of $\mathbf{P}_{l_m}$, the probabilities that appear (implicitly) on the right hand side of equation (9)[16]. These estimates ($\widehat{\mathbf{P}}_{l_m}$) are then used to construct the ρ's, which are then plugged into the likelihood function. Maximization of this (pseudo) likelihood constitutes the second stage of the procedure. Consistency and asymptotic normality has been established for a broad class of two-step estimators by Newey and McFadden (1994), while Bajari et al. (2005) provide formal results for the model estimated here.

5.4 The Likelihood

In our econometric implementation, we will assume that ζ and ξ are independent, mean zero normal errors, so that

$$F\left(\xi_c^m(k), \zeta_c(k); \Omega\right) = F_\xi\left(\xi_c^m(k); \Omega_\xi(k)\right) \times F_\zeta\left(\zeta_c(k); \Omega_\zeta(k)\right), \tag{11}$$

where both F_ξ and F_ζ are mean zero normal distribution functions with finite covariance matrices. For simplicity, we also assume that the covariance matrices are diagonal with elements $\tau_\zeta^2(k)$ and $\tau_\xi^2(k)$. For identification, consistent with our earlier independence and normalization assumptions, we will assume that $\xi_c^m(P) = \zeta_c(P) = 0 \; \forall \; c \in C, m \in M$. These assumptions allows us to use a simulated maximum likelihood procedure that replaces (10) with its sample analog

$$\tilde{\mathcal{L}}(\Theta) = \prod_{m\in M} R_\zeta^{-1} \sum_{r_\zeta=1}^{R_\zeta} \prod_{c\in C} \left[R_\xi^{-1} \sum_{r_\xi=1}^{R_\xi} \left\{ \prod_{l_m\in L_m} \prod_{i_c^{l_m}\in N_c^{l_m}} \left[\Psi_{i_c^{l_m}}\left(a_{i_c^{l_m}} = k | \mathbf{\Theta}, \widehat{\mathbf{P}}_{l_m}, \mathbf{s}, \xi_c^m(k), \zeta_c(k) \right) \right]^{\delta_{i_c^{l_m}}(k)} \right\} \right]. \tag{12}$$

In the simulation procedure, $[\xi_c^m(k)]_{r_\xi}$ and $[\zeta_c(k)]_{r_\zeta}$are drawn from mean zero normal densities with variances $\tau_\xi^2(k)$ and $\tau_\zeta^2(k)$ respectively. We use $R_\xi = R_\zeta = 500$ and maximize (12) to obtain estimates of the structural parameters. Note that the fixed point restriction,

[16] The ρ's are functions of $\mathbf{P}_{l_m}$.

$\mathbf{P}_{l_m} = \Psi_{l_m}$, no longer appears since we have replaced $\mathbf{P}_{l_m}$ with $\widehat{\mathbf{P}}_{l_m}$ in the formulas for $\rho^{EDLP}_{-i_c^{l_m}}$ and $\rho^{PROMO}_{-i_c^{l_m}}$, which are used in constructing $\Psi_{i_c^{l_m}}$ (see 9). We now move to a discussion of how we estimate beliefs.

5.5 Estimating Beliefs

In an ideal setting, we could recover estimates of each store's beliefs regarding the conditional choice probabilities of its competitors using fully flexible non-parametric methods (e.g. kernel regressions or sieve estimators). Unfortunately, given the large number of covariates we have included in our state vector, these methods are infeasible here. Instead, we employ a parametric approach for estimating $\hat{\rho}_{-i_c^{l_m}}$, using a mixed multinomial logit (MNL) specification to recover these first stage choice probabilities (Appendix A.3 contains a semi-parametric robustness analysis). Note that this is essentially the same specification employed in the second stage procedure (outlined above), only the store's beliefs regarding rival's actions are excluded from this initial reduced form. Note that we do not require an explicit exclusion restriction, since our specification already contains natural exclusion restrictions due to the presence of state variables that vary across stores and chains.

We implement an estimator similar to (12), but with the coefficients on the ρ's (i.e. α's) set to zero. Let the parameters in the first stage be denoted by $\Lambda_1 = \{\beta_1, \Omega_1\}$[17] and the first stage likelihood for a given store be denoted by $\mathcal{L}_{i_c^{l_m}}(\Lambda, \xi_c^m(k), \zeta_c(k))$. Using a simulated maximum likelihood approach, we obtain $\hat{\Lambda}_1$, the maximum (simulated) likelihood estimate of Λ_1. Given these estimates, and applying Bayes' rule, the posterior expectation of $P(a_{i_c^{l_m}} = k|s, \xi_c^m(k), \zeta_c(k))$ can be obtained via the following computation

$$\frac{\int\limits_{\zeta}\int\limits_{\xi} \Psi_{i_c^{l_m}}\left(a_{i_c^{l_m}} = k|\hat{\Lambda}, \xi_c^m(k), \zeta_c(k)\right) \mathcal{L}_{i_c^{l_m}}\left(\hat{\Lambda}, \xi_c^m(k), \zeta_c(k)\right) dF\left(\xi_c^m(k), \zeta_c(k); \hat{\Omega}_1(k)\right)}{\int\limits_{\zeta}\int\limits_{\xi} \mathcal{L}_{i_c^{l_m}}\left(\hat{\Lambda}, \xi_c^m(k), \zeta_c(k)\right) dF\left(\xi_c^m(k), \zeta_c(k); \hat{\Omega}_1(k)\right)}. \tag{13}$$

While this expression is difficult to evaluate analytically, the vector of beliefs defined by $\hat{\rho}^{(k)}_{i_c^{l_m}} = \mathcal{E}_{\{\zeta,\xi\}}\left[\Psi_{i_c^{l_m}}\left(a_{i_c^{l_m}} = k|\hat{\Lambda}, \xi_c^m(k), \zeta_c(k)\right)\right]$ can be approximated by its simulation

[17] The subscript 1 denotes that these are first stage estimates.

analog

$$\hat{\rho}^{(k)}_{i^{lm}_c} \simeq \frac{\sum_{r=1}^{R} \Psi_{i^{lm}_c}\left(a_{i^{lm}_c} = k|\hat{\Lambda}, [\xi^m_c(k), \zeta_c(k)]_r\right) \mathcal{L}_{i^{lm}_c}\left(\hat{\Lambda}, [\xi^m_c(k), \zeta_c(k)]_r\right)}{\sum_{r=1}^{R} \mathcal{L}_{i^{lm}_c}\left(\hat{\Lambda}, [\xi^m_c(k), \zeta_c(k)]_r\right)}. \tag{14}$$

in which $[\xi^m_c(k), \zeta_c(k)]_r$ are draws from a distribution $F\left(\xi^m_c(k), \zeta_c(k); \hat{\Omega}\right)$ with similar properties to those described in Section 5.4. Again, we use $R = 500$ simulation draws. Recalling that $k \in K = \{E, H, P\}$, we can now define a consistent estimator of $\rho^{(k)}_{-i^{lm}_c}$ as

$$\hat{\rho}^{(k)}_{-i^{lm}_c} = \left(\sum_{v \neq c} N^{l_m}_v\right)^{-1} \sum_{h \neq i^{lm}_c} \hat{\rho}^{(k)}_h. \tag{15}$$

We note in passing that the consistency of our estimator is maintained even with the inclusion of two types of random effects, since these variables are treated as private information of each store. As noted earlier, allowing for random effects that are common knowledge to the players, but unobserved to the econometrician (e.g. market level heterogeneity) would violate the *i.i.d.* assumption required for consistency of the two-step estimation procedure.[18] However, we will relax this assumption below in one of our robustness checks. A final note relates to the construction of standard errors. Since the two-step approach precludes using the inverse information matrix, we employ a bootstrap approach instead.[19]

5.6 Identification

Bajari et al. (2005) establish identification of the structural parameters of a discrete game provided three assumptions are satisfied. The first two have already been (implicitly) stated, but will be repeated here more formally. The first assumption is that the error terms ϵ_i are distributed *i.i.d.* across players and actions in any given market[20], and are drawn from a

[18] Bajari et al. (2005) suggest using "fixed effects" which are restricted to be smooth functions of the observed state variables. We do not have enough data to estimate their non-parametric first stage and prefer an approach based on Aguirregabiria and Mira's (2006) Nested Pseudo Likelihood approach to control for location specific unobservables.

[19] In particular, we bootstrapped across markets (not individual stores) and held the pseudorandom draws in the simulated likelihood fixed across bootstrap iterations. To save time we used the full data estimates as starting values in each bootstrap iteration.

[20] Note that the *iid* requirement only needs to hold at the market level. For example, it's fine to include random effects in the error term, provided these effects are treated as private information of the particular store in question. This is in fact the approach we adopt below.

distribution of known parametric form. This is clearly satisfied by the assumptions imposed above. The second assumption requires that the expected profit associated with one strategy be normalized to zero. This is a standard normalization required to identify any multinomial choice model. We normalize the mean profit of the PROMO strategy to zero. The final assumption is an exclusion restriction.

The reason for imposing an exclusion restriction can be illustrated using equation (9). Our two-step estimation procedure involves estimating the shares (ρ's) on the right hand side of (9) in a first stage. These shares, which are simple functions of each firm's beliefs regarding the conditional choice probabilities of its rival's (via the ρ's in (9)), depend on the same state vector (s) as the first term of the profit function ($s'\beta_k$), creating a potential identification problem. Note that identification can be trivially preserved by the non-linearity of the discrete choice problem, although this follows directly from functional form. A non-parametric alternative, suggested by Bajari et al. (2005), is to identify one or more continuous covariates that enter firm i's payoffs, but do not enter the payoffs of any competing firm. This exclusion restriction ensures that both the payoffs and the estimates of firms' beliefs regarding the actions of their rivals are identified. Bajari et al. (2005) suggest using the idiosyncratic shocks of rival firms as the exclusion. Since our state vector varies across stores and chains, we have a natural exclusion restriction which is similar in spirit to this idea. In other words, while the state variables are the same they do not contain the same values across stores and chains. This results in different patterns of variation in the ρ's and the profit component related to state variables ($s'\beta_k$) helping identify the parameters cleanly.[21] Identification of all other parameters is straightforward and we do not discuss them here. Having described both our theoretical model and empirical strategy, we now present our main results.

6 Results and Discussion

As noted earlier, choosing an optimal pricing strategy is a complex task, forcing firms to balance the preferences of their customers against the strategic actions of their rivals. A major advantage of our two-step estimation approach is that, by estimating best response

[21] We are indebted to Victor Aguirregabiria and Han Hong for helpful discussions on this topic and to Victor in particular for pointing out the presence of natural exclusion restrictions in our model.

functions rather than equilibrium correspondences, we can separately identify strategic interactions, reactions to local and market level demographics, and operational advantages associated with larger stores and proprietary distribution systems. Our empirical results highlight each of these forces. First, we find that firms choose strategies that are tailored to the demographics of the market they serve. Moreover, the impact of demographics corresponds closely to existing empirical studies of consumer preferences and conventional wisdom regarding search behavior. Second, we find that the EDLP strategy is favored by firms that operate larger stores and are vertically integrated into distribution. Again, this accords with conventional wisdom regarding the main operational advantages of EDLP. Finally, with regard to strategic interaction, we find that firms coordinate their actions, choosing pricing strategies that match their rivals. This identifies an aspect of firm behavior that has not been addressed in the existing literature: exactly how firms react to rival strategies.

Our main empirical results are presented in Table 6. The coefficients, which represent the parameters of the profit function represented in equation (6), have the same interpretation as those of a standard MNL model: positive values indicate a positive impact on profitability, increasing the probability that the strategy is selected relative to the outside option (in this case, PROMO).

6.1 The Role of Demographics

The coefficients on consumer demographics are presented in the second and third sections of Table 6. With the exception of two MSA-level covariates, every demographic factor plays a significant role in the choice of EDLP as a pricing strategy. This is important from an econometric standpoint, since we use these very same factors to construct expectations in the first stage. In particular, the significance of the estimates means that we do not have to worry about collinearity. The statistical significance of the parameters is also substantively important. It suggests that the even after accounting for competitive and supply side (store/chain) characteristics, consumer demand plays a strong role in the determination of pricing strategy.

Focusing more closely on the demand related parameters, we find that (relative to PROMO), EDLP is the preferred strategy for geographic markets that have larger households $\left(\beta^{HH} = 0.5566\right)$, more racial diversity in terms of African-American $\left(\beta^{BL} = 0.6833\right)$ and Hispanic $\left(\beta^{HI} = 0.5666\right)$ populations, lower income $\left(\beta^{INC} = -0.0067\right)$, and fewer vehicles per household $\left(\beta^{VH} = -0.1610\right)$. These results suggest that EDLP is mostly aimed at lower income consumers with larger families (i.e. more urbanized areas). Our findings are clearly consistent with the consumer segments that firms like Wal-Mart are widely perceived to target. It also accords quite well with the Bliss/Bell & Lattin model of fixed basket shopping behavior, in which consumers who are more sensitive to the price of an overall basket of goods prefer EDLP. In particular, our results suggest that the consumers who are unable to substitute inter-temporally are disproportionately poor, from non-white demographic groups, and from larger families. On the other hand, we find that consumers who are most able to defer or stockpile purchases (wealthy suburbanites with greater access to transportation) are likely to prefer PROMO or HYBRID pricing.

6.2 Firm and Store Level Characteristics

Turning next to chain and store level characteristics, we again find that most parameter estimates are statistically significant. These effects, which are in line with both theory and broad intuition, provide an additional empirical validation of our structural framework.

The last two sections of Table 6 show that stores choosing EDLP are both significantly larger $\left(\beta^{SS} = 0.0109\right)$ and far more likely to be vertically integrated $\left(\beta^{VI} = 0.1528\right)$ into distribution. This is consistent with the view that EDLP requires substantial firm level investment, careful inventory management, and a deeper selection of products in each store. It is also consistent with the model of Lal and Rao (1997), in which pricing strategy involves developing an overall positioning strategy, requiring complementary investments in store quality and product selection. Surprisingly, the total number of stores in the chain is negatively related to EDLP $\left(\beta^{ST} = -0.0002\right)$, although this is difficult to interpret since almost all the large chains are vertically integrated into distribution (so there are almost no large, non-vertically integrated firms). Finally, both the chain specific and chain/MSA random effects are highly significant, which is not surprising given the geographic patterns shown earlier.[22]

[22] An earlier version of this paper also included the share of each firm's stores outside the local MSA that employ EDLP and PROMO pricing as additional regressors. Not surprisingly, a firm's propensity to follow a particular strategy at the level of the chain had a large and significant impact on its strategy in a particular

6.3 The Role of Competition: Differentiation or Coordination

By constructing a formal model of strategic interaction, we are able to address the central question posed in this paper - what is impact of competitive expectations on the choice of pricing strategy? Our conclusions are quite surprising. The first section of Table 6 reveals that firms facing competition from a high (expected) share of EDLP stores are far more likely to choose EDLP than either HYBRID or PROMO ($\hat{\sigma}^{EDLP}_{-i^{l_m}_c} = 4.4279, \hat{\sigma}^{PROMO}_{-i^{l_m}_c} = -3.7733$). The HYBRID case behaves analogously; when facing a high proportion of either EDLP or PROMO rivals, a store is least likely to choose HYBRID ($\hat{\sigma}^{EDLP}_{-i^{l_m}_c} = -2.0924, \hat{\sigma}^{PROMO}_{-i^{l_m}_c} = -6.3518$). In other words, we find no evidence that firms differentiate themselves with regard to pricing strategy. To the contrary, we find that rather than isolating themselves in strategy space, firms prefer to coordinate on a single pricing policy.

This coordination result stands in sharp contrast to most formal models of pricing behavior, which (at least implicitly) assume that these strategies are vehicles for differentiation. Pricing strategy is typically framed as a method for segmenting a heterogeneous market - firms soften price competition by moving further away from their rivals in strategy space. This is not the case for supermarkets. Instead of finding the anti-correlation predicted by these 'spatial' models, we find evidence of associative matching, which usually occurs in settings with network effects or complementarities. This suggests that firms can increase the overall level of demand by matching their rivals' strategies, a possibility we discuss in more detail in what follows.

Before discussing our coordination result in greater detail, we must address the issue of common unobservables. Of obvious concern is whether firms are actually reacting to the actions of their rivals, or simply optimizing over some common but unobserved features of the local market. Manski (1993) frames this as the problem of distinguishing endogenous effects from correlated effects.[23] While the presence of both effects yields collinearity in the linear in means model examined there (i.e. the reflection problem), the non-linearity

store (and soaked up a lot of variance). While this suggests the presence of significant scale economies in implementing pricing strategies, as suggested in both Lattin and Ortmeyer (1991) and Hoch et al. (1994), we omitted it from the current draft in order to maintain the internal coherency of the underlying model (i.e. the simultaneity of actions).

[23] Manski (1993) also considers the role of contextual effects, whereby the "propensity of an individual to behave in some way varies with the distribution of background characteristics of the group". The static setting of our game eliminates this third type of "social interaction".

of the discrete choice framework eliminates this stark non-identification result. However, the presence of correlated unobservables remains a concern, so we extended our framework to include a location specific unobservable. To do so, we implemented a static version of Aguirregabiria and Mira's (2006) Nested Pseudo-Likelihood (NPL) estimator.[24] The main coordination results are presented in columns 4 and 5 of Table 7 (the demographic and chain level covariates have been suppressed for brevity). While the magnitudes of the coefficients do fall relative to the baseline specification (as expected), the coordination effects are still large and significant.

While our main focus is on the parameters of the best response functions, it is important to clarify what our coordination result implies about the structure of the pricing game. As a simplification, consider two stores playing a game with a 3×3 payoff matrix based on pricing policy. Our empirical results indicate that the equilibria are concentrated on the diagonal cells, meaning that firms receive larger payoffs when they coordinate. Intuitively, this has the flavor of a "Battle of the Sexes" game with three choices, in which the players would like to coordinate on a single activity - their pricing strategy. However, in this pricing game, the payoff matrix depends on market demographics, which can facilitate coordination. For example, firms may coordinate on EDLP in some markets (e.g. low income), but favor PROMO in others (e.g. high income).[25]

It is worth emphasizing that reactions to market demographics and firm characteristics help explain *how* firms are able to coordinate on consistent strategies. However, they do not explain *why* they choose to do so. Coordination implies that firm's conditional choice probabilities act as strategic complements, meaning that their best response functions (9) are upward sloping. To support complementarity, coordination must somehow increase the overall size of the pie that firms are splitting (by drawing expenditures away from the outside good).

[24] Since the NPL estimator iterates on the fixed point mapping, it does not require a consistent first stage estimate of the choice probabilities (which is why it can incorporate a location specific unobservable). However, a drawback of this approach is that it is not always guaranteed to converge and requires the existence of a contraction around every relevant equilibria (Judd and Su, 2006).

[25] Another possibility is that firms might exploit the geographic structure of the game (i.e. their opponents behavior in other markets) as a signaling device to facilitate coordination. This type of equilibrium has some of the flavor of a correlated equilibrium (e.g. Aumann, 1974), with spatial dependence playing the role of time. Formalizing this conjecture is beyond the scope of this paper, but is an intriguing topic for future research.

In the context of supermarket pricing, this suggests that coordination may actually increase the amount consumers are willing to spend on groceries, perhaps by drawing them away from substitutes like restaurants, convenience stores, and discount clubs. One way this might occur in practice is if consumers are more likely to "trust" retailers that provide a message that is consistent with those of their rivals. In other words, if one firm tells you that providing the highest value involves high price variation while another touts stable prices, you may be unwilling to trust either, shifting your business to a discount club or another retail substitute. While this intuition has yet to be formalized, it is consistent with the emphasis that Ortmeyer et al. (1991) place on maintaining "pricing credibility". Another possibility, consistent with Lal and Rao (1997), is that price positioning is multidimensional and by coordinating their strategies stores can mitigate the costs of competing along several dimensions at once. Without a formal model of consumer behavior and detailed purchase data, we are unable to pin down the exact source of the complementarities we have documented here. However, we have provided strong empirical evidence regarding how firms actually behave. Understanding why firms find it profitable to coordinate their actions remains a promising area for future theoretical research.

The results presented above provide definitive answers to the three questions posed in the introduction of this paper. We have found that demand related factors (i.e. demographics) are important for determining the choice of pricing strategy in a market; store and firm level characteristics also play a central role. Both of these results are in line with the extant literature. However, our results concerning competitive expectations are in sharp contrast to prevailing theory in both economics and marketing and warrant further attention. The final section outlines a research agenda for extending the results found in this paper.

7 Conclusions and Directions for Future Research

This paper analyzes supermarket pricing strategies as discrete game. Using a system of simultaneous discrete choice models, we estimate a firm's optimal choice conditional on the underlying features of the market, as well as each firm's beliefs regarding its competitor's actions. We find evidence that firms cluster by strategy, rather than isolating themselves in product space. We also find that demographics and firm characteristics are strong determinants of pricing strategy. From a theoretical perspective, it is clear that we have yet to fully understand what drives consumer demand. The fact that firms coordinate with their rivals suggests that consumers prefer to receive a consistent message. While our results pertain most directly to supermarkets, it seems likely that other industries could behave similarly. Future research could examine the robustness of our findings by analyzing other retail industries, such as department stores or consumer electronics outlets.

In this paper, our primary focus was the construction and econometric implementation of a framework for analyzing best responses to rival pricing strategies. Our analysis describes the nature of strategic interactions, but does not delve into the details of why these strategies are dominant. Decomposing the *why* element of strategic coordination seems a fruitful area of research. We hasten to add that such research is needed not only on the empirical side but also on the theoretical front. Building theoretical models that allow for the possibility of both differentiation and coordination is a challenging but likely rewarding path for future research.

The tendency to coordinate raises the possibility that games such as this might support multiple equilibria. While this is not a concern in our current study, it could play a central role when conducting policy experiments or when analyzing settings in which demographics (or other covariates) cannot effectively facilitate coordination. Developing methods that are robust to such possibilities remains an important area for future research.

Finally, in building our model of strategic interaction, we have assumed that firms interact in a static setting, making independent decisions in each store. A more involved model would allow chains to make joint decisions across all of their outlets and account for richer (dynamic) aspects of investment. Developing such a model is the focus of our current research.

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A Robustness Checks

In this appendix, we examine the robustness of our results to alternative specifications and distributional assumptions. In particular, we focus on (1) market definition, (2) non-parametric estimation of beliefs, (3) linearity of the response functions and (d) the parametric error structure.

A.1 Market Delineation and Definition

As noted earlier, our empirical analysis uses specific market definitions based on spatial cluster analysis. We verified the robustness of our results to alternative market definitions by repeating the analysis using ZipCodes, Counties, and MSAs. In all cases, the results were qualitatively similar. We also varied the number of clusters and again found no significant differences in the results reported above.

A.2 Multiplicity

As we noted earlier, consistent estimation of a static (or dynamic) game requires some form of uniqueness of equilibrium, either in the model or in the data.[26] Consistency of our baseline model requires only one equilibrium be played in the data, which, in our context, means every location in every MSA. It is possible to relax this by estimating the first stage separately for each MSA, so the requirement becomes a unique equilibrium be played in each MSA (we do not have enough data to estimate the first stage separately for each cluster, which would eliminate the problem entirely). The results of this procedure were very close to the baseline model. For brevity, we report only the coefficients on the strategy variables (in columns 6 and 7 of Table 7).

A.3 Nonparametric Estimation of ρ_{-i}

As noted above, the ideal approach for estimating beliefs involves non-parametric techniques. However, the number of covariates we use precludes us from adopting such a

[26] Uniqueness may fail to hold in many settings. Brock and Durlauf (2001) and Sweeting (2004) provide two such examples. Non-uniqueness can complicate policy experiments, which typically involve solving for a new equilibrium. While we do not conduct any policy experiments in this paper, Bajari et al. (2005) demonstrate how the homotopy continuation method can be used to simulate multiple equilibria in a setting similar to ours.

strategy. To assess the robustness of our results, we used a bivariate thin-plate spline to model pricing strategies as non-parametric functions of the strategies chosen outside the MSA. Again, the main results were qualitatively similar to those presented above.

A.4 Nonlinearity of $f\left(\rho_{-i}\right)$

To examine the potentially non-linear relationship between payoffs (Π) and strategies $\left(\rho_{-i}\right)$, we adopted a smoothing splines approach to modeling $f(\rho_{-il})$. In particular, we re-estimated our model using a bivariate thin-plate spline, treating the functional relationship as

$$f_j(a_{-i_c^{lm}}) = f\left(\rho^E_{-i_c^{lm}}, \rho^P_{-i_c^{lm}} | \varpi\right) \tag{16}$$

The qualitative results obtained using the linear specification continue to hold. Since the results for the other variables are similar, we will not repeat our earlier discussion of their effects here but focus only on the strategic results pertaining to pricing strategy. In particular, we focus our attention on the EDLP case to illustrate our findings. Figure 4 depicts the smoothed functional relation between beliefs about competitor strategy and the probability of choosing EDLP. As with the linear specification, we observe evidence of firms collocating in strategy space. The probability of firms choosing EDLP increases with the proportion of competitors that also choose EDLP.

A.5 Error Structure

In our analysis we assumed that firm types (the ϵ_i's) were distributed Gumbel (Type I Extreme Value), allowing us to specify set of simultaneous multinomial logit choice probabilities for determining pricing policies. As an alternative specification, similar to the empirical application in Bajari et al. (2005), we also tested ordered logit/probit models in which the strategies were ranked on a EDLP-HYBRID-PROMO continuum. While qualitative findings were similar, these ordered specifications force a particular ordering of the strategies that may not be warranted.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min.	Max
Strategy					
EDLP	17388	0.28	0.45	0	1
HYBRID	17388	0.38	0.48	0	1
PROMO	17388	0.34	0.47	0	1
MSA Characteristics					
Size (sq. miles)	333	1868.31	1943.99	46.4	11229.6
Density (pop '000 per sq. mile)	333	10.42	9.62	0.91	49.06
Avg. Food Expenditure ($ '000)	333	663.64	1201.37	16.04	9582.09
Market Variables					
Median Household Size	8000	2.66	0.35	1.32	5.69
Median HH Income	8000	35255.59	9753.95	18109.60	81954.60
Proportion Black	8000	0.08	0.14	0.00	0.97
Proportion Hispanic	8000	0.06	0.13	0.00	0.98
Median Vehicles in HH	8000	2.12	0.33	0.56	3.37
Chain/ Store Characteristics					
Vertically Integrated	17388	0.51	0.50	0.00	1.00
Store Size (sqft '000)	17388	28.99	16.34	2.00	250.00
Independent Store	17388	0.23	0.42	0.00	1.00
Number of Stores in Chain	804	390.15	478.45	1.00	1399.00

Table 2: Pricing Strategies by Region

Region	% PROMO	% HYBRID	% EDLP
West Coast	39	39	22
Northwest	32	51	17
South West	20	48	32
South	32	25	43
Southern Central	45	27	28
Great Lakes	54	29	17
North East	40	37	23
South East	23	37	40

Table 3: Pricing Strategies of the Top 15 Supermarkets

Firm	Stores	% PROMO	% HYBRID	% EDLP
Kroger	1399	47	40	13
Safeway	1165	52	43	5
Albertson's	922	11	41	48
Winn-Dixie	1174	3	30	67
Lucky	813	35	38	27
Giant	711	29	60	11
Fred Meyer	821	22	60	18
Wal-Mart	487	1	26	73
Publix	581	13	71	16
Food Lion	1186	2	12	86
A&P	698	55	30	15
H.E. Butt	250	1	3	96
Stop & Shop	189	50	43	7
Cub Foods	375	26	34	40
Pathmark	135	42	25	33

Table 4: Pricing Strategy by Firm Type

"Large" Firms:	% EDLP	% HYBRID	% PROMO
Chain	33	37	30
Vertically Integrated	35	36	29
Large Store Size	32	38	30
Many Checkouts	31	39	30
"Small" Firms:	**% EDLP**	**% HYBRID**	**% PROMO**
Independent	22	28	50
Not Vertically Integrated	21	32	47
Small Store Size	23	26	52
Few Checkouts	22	26	52

Table 5: Local Factors

	EDLP	HYBRID	PROMO
Local Demographics			
Median Household Size	2.84 (.331)	2.81 (.337)	2.80 (.329)
Median Household Income	34247 (14121)	36194 (15121)	36560 (16401)
Median Vehicles in HH	2.12 (.302)	2.13 (.303)	2.09 (.373)
Median Age	35.4 (4.59)	35.8 (4.98)	35.7 (4.25)
Proportion Black	.128 (.182)	.092 (.158)	.110 (.185)
Proportion Hispanic	.078 (.159)	.073 (.137)	.070 (.135)
Strategies of Rivals			
% of Rivals Using Same Strategy	49 (31)	49 (25)	52 (23)

The main numbers in each cell are means. Standard deviations are in parentheses.

Table 6: Estimation Results

	EDLP			HYBRID		
Effect	**Estimate**	**Std. Err**	**T-Stat**	**Estimate**	**Std. Err**	**T-Stat**
Intercept	-1.5483	0.2426	-6.3821	2.1344	0.2192	9.7372
Strategy Variables						
$\widehat{\sigma}^{EDLP}_{-i_c^{lm}}$	4.4279	0.1646	26.9010	-2.0924	0.1595	-13.1185
$\widehat{\sigma}^{PROMO}_{-i_c^{lm}}$	-3.7733	0.1501	-25.1386	-6.3518	0.1351	-47.0155
MSA Characteristics						
Size ('000 sq. miles)	0.0394	0.0848	0.4645	-0.0566	0.0804	-0.7039
Density (pop 10,000 per sq. mile)	-0.0001	0.0002	-0.4587	0.0006	0.0002	2.9552
Avg. Food Expenditure ($ '000)	-0.0375	0.0155	-2.4225	-0.0013	0.0141	-0.0904
Market Variables						
Median Household Size	0.5566	0.1989	2.7983	0.2150	0.0900	2.3889
Median HH Income	-0.0067	0.0019	-3.5385	0.0056	0.0017	3.2309
Proportion Black	0.6833	0.1528	4.4719	0.0139	0.1443	0.0963
Proportion Hispanic	0.5666	0.2184	2.5943	-0.0754	0.2033	-0.3708
Median Vehicles in HH	-0.1610	0.0840	-1.9167	0.2263	0.1173	1.9292
Store Characteristics						
Store Size (sqft '000)	0.0109	0.0015	7.2485	0.0123	0.0014	8.8512
Vertically Integrated	0.1528	0.0614	2.4898	0.0239	0.0550	0.4343
Chain Characteristics						
Number of Stores in Chain	-0.0002	0.0001	-2.7692	0.0002	0.0001	3.5000
Chain Effect	1.7278	0.0998	17.3176	2.8169	0.0820	34.3531
Chain/MSA Effect	0.7992	0.0363	22.0408	0.9968	0.0278	35.8046

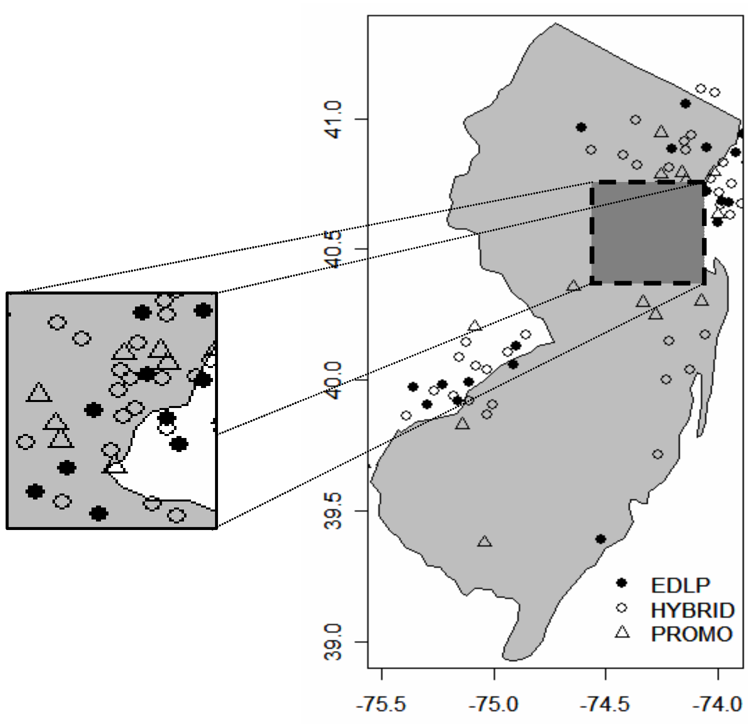

Figure 1: Pathmark Stores in New Jersey

Table 7: Robustness

Specification	Strategy	Strategy Variables $\widehat{\sigma}^{EDLP}_{-i_c^{lm}}$	$\widehat{\sigma}^{PROMO}_{-i_c^{lm}}$
Baseline	EDLP	4.4279 (0.1646)	−3.7733 (0.1501)
	HYBRID	−2.0924 (0.1595)	−6.3518 (0.1351)
NPL	EDLP	1.7464 (0.1743)	−2.5699 (0.1723)
	HYBRID	−0.7365 (0.1770)	−4.9899 (0.1739)
MSA by MSA	EDLP	3.1867 (0.2522)	−3.2823 (0.1771)
	HYBRID	−3.4418 (0.2603)	−6.2746 (0.1701)
Pure Logit	EDLP	4.3399 (0.1564)	−3.6577 (0.1435)
	HYBRID	−1.9710 (0.1498)	−6.5537 (0.1255)

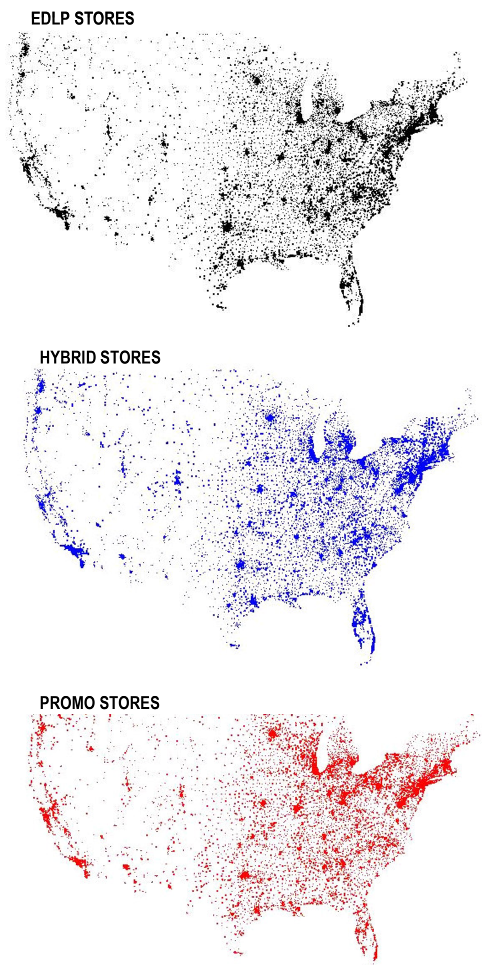

Figure 2: Spatial Distribution of Store Pricing Strategy

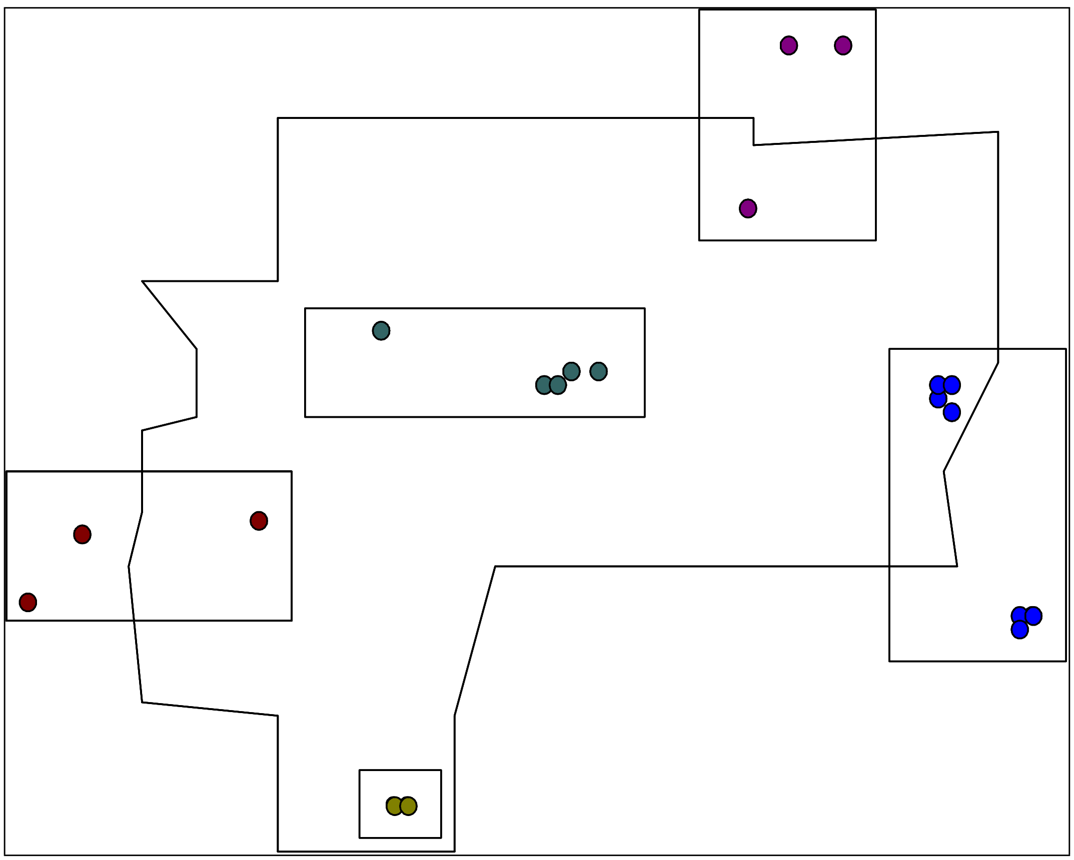

Figure 3: Store clusters in Ontario County, NY

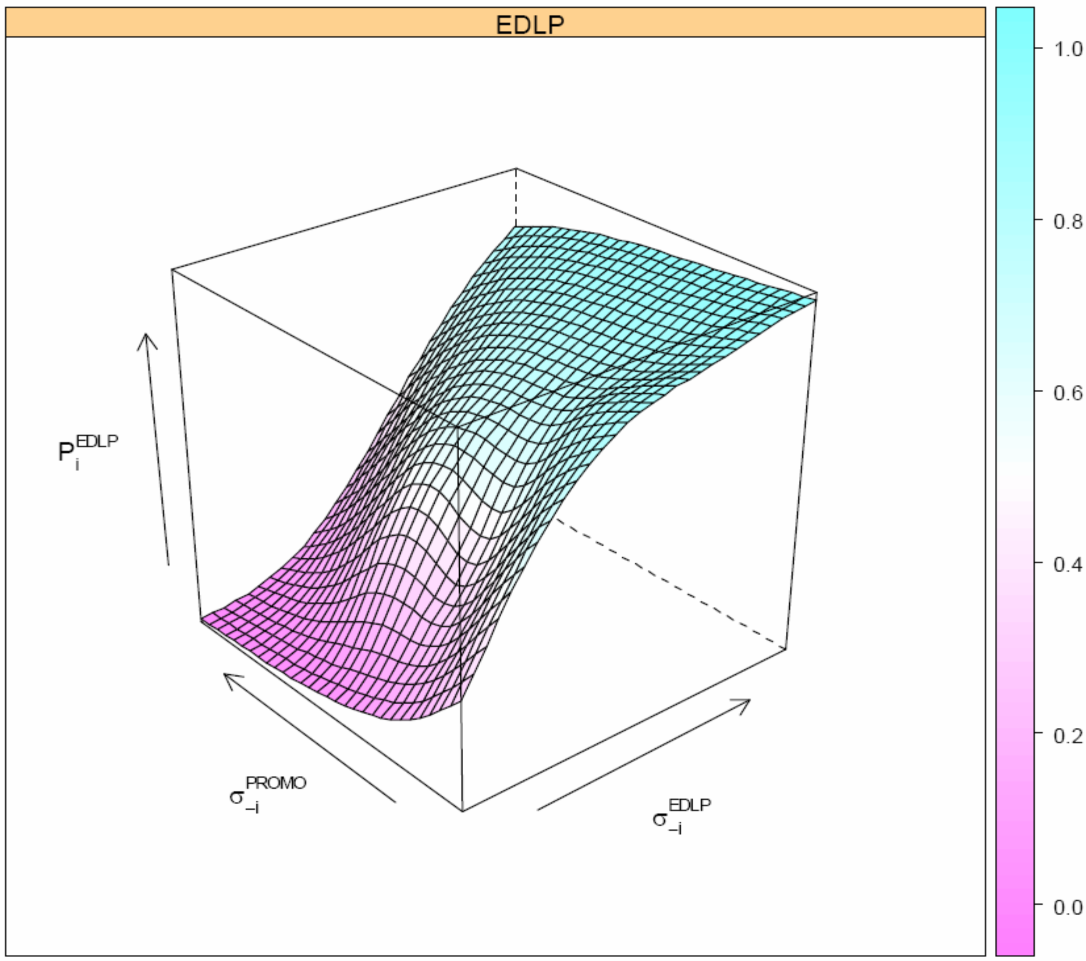

Figure 4: Probability of choosing EDLP as a function of beliefs regarding a rival's strategy.