Repositioning Dynamics and Pricing Strategy*

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Abstract

We measure the revenue and cost implications to supermarkets of changing their price positioning strategy in oligopolistic downstream retail markets. Our approach formally incorporates the dynamics induced by the repositioning in a model with strategic interaction. We exploit a unique dataset containing the price-format decisions of all U.S. supermarkets in the 1990s. The data contain the format-change decisions of supermarkets in response to a large shock to their local market positions: the entry of Wal-Mart. We exploit the responses of retailers to Wal-Mart entry to infer the cost of changing pricing-formats using a "revealed-preference" argument similar in spirit to Bresnahan and Reiss (1991). The interaction between retailers and Wal-Mart in each market is modeled as a dynamic game. We find evidence that entry by Wal-Mart had a significant impact on the costs and incidence of switching pricing strategy. Our results add to the marketing literature on the organization of retail markets, and have implications for long-run market structure in the supermarket industry. Our approach, which incorporates long-run dynamic consequences, strategic interaction, and sunk investment costs, may be used to model empirically firms' *positioning* decisions in Marketing, more generally.

Keywords: Positioning, dynamic games, EDLP, PROMO, pricing, supermarkets, Wal-Mart.

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1 Introduction

Large changes to some or all of a firm's Marketing apparatus are referred to as "repositioning." While common in product markets and extensively discussed in management textbooks (e.g., Ries and Trout (1981)), empirical analysis of repositioning decisions in the academic literature has remained scarce. Perhaps the most visible forms of repositioning are brand related. Recent examples include Domino Pizza's attempt to switch their reputation from fast delivery to high quality, and the repositioning of UPS from shipping to full office solutions. Other examples include adjustments to product lines, such as Hyundai's recent move into the luxury auto segment in the U.S. or Kodak's long-delayed transition to digital imaging. While brand related changes are common, they are far from the only examples. Apple's inclusion of third party retailers can be thought of as repositioning their downstream distribution strategy, while Proctor and Gamble's adoption of "Value-Based Pricing" in 1992 to reduce trade-promotions, was a repositioning of their overall pricing strategy (Ailawadi, Lehmann, and Neslin (2001)). St-James (2001) describes several instances of repositioning by firms in US consumer product markets, including a detailed history from the 1920s of attempts by Sears, Wards and J.C. Penny chain stores to periodically reposition themselves in response to changing consumer tastes and competition.

Repositioning is different from new entry as it is inherently history-dependent: repositioning typically requires incurring costs to undo past product related decisions. Therefore, repositioning costs to incumbents can often be *much larger* than the cost of entry to new firms. Repositioning frequently involves complex investments needed to overcome within-firm managerial resistance to change, to rework channel relationships, and to educate (and advertise to) consumers about the new positioning, all investments that are large and sunk. The magnitude of repositioning costs have substantive implications for competition and market structure. Low repositioning costs help constrain market power by enabling competitors to react faster to changes in a firm's product-lines and product attributes. When repositioning investments are sunk, they also have commitment value (Dixit and Pindyck (1994)), implying current repositioning decisions can affect long-run market outcomes such as the future entry and exit behavior of rival firms. Hence, measuring repositioning costs are important to understanding the economic underpinnings of market structure in an industry.

In this paper we examine the repositioning of the pricing strategies of U.S. supermarket firms. Our empirical goals are to measure the revenue and cost implications to supermarkets of changing their store-level pricing formats. These pricing formats are broadly split between EDLP (Every Day Low Price) and PROMO (or promotional) strategies.[1] EDLP stores charge a low regular price per product with little temporal price variation, while PROMO stores are characterized by higher regular prices, punctuated by frequent price promotions or "sales." A store's choice between EDLP or PROMO is motivated by both demand- and cost-side considerations. On the demand side, choosing PROMO over EDLP offers an opportunity for supermarkets to intertemporally price discriminate, by using price cycles to sell differentially to consumers of varying price information, loyalty, stockpiling costs or valuations (Varian (1980); Salop and Stiglitz (1982); Sobel (1984); Lal and Rao (1997); Pesendorfer (2002); Bell and Hilber (2006)). Further, the frequent price variation under PROMO may create an option value to consumers of visiting the store more frequently by reducing their average basket size per trip (Bell and Lattin (1998); Ho, Tang, and Bell (1998)). On the cost-side, EDLP enables retailers to reduce inventory costs, to better coordinate supply-chains, and to reduce stock-out risk by smoothing the demand variability induced by frequent sales. The choice of EDLP or PROMO is an important strategic choice faced by retailers that affects their price image, with significant long-term implications for profitability and local market structure (Lal and Rao (1997); Ellickson and Misra (2008)).

Several factors may cause a supermarket chain to change its store pricing format in a local market. One first-order factor is response to competitive entry, especially by rivals with a comparative advantage in a particular strategy. Our data, which covers a census of supermarket entry, exit, revenue and format choices in the 1990s, includes a period of intense readjustment in response to a one such event: the introduction of Wal-Mart supercenters, which exclusively follow an EDLP strategy. The entries of Wal-Mart supercenters serve as large shocks to the competitive structure of local markets, inducing a large number of format switches and a host of exits. Our identification of repositioning costs exploits these switches heavily, and rests on a revealed preference argument

[1] PROMO is also referred to as "HiLo."

similar to that of Bresnahan and Reiss (1991) and Bresnahan and Reiss (1994): if we see that a firm switched its price positioning, it has to be that the profits (in a present-discounted sense) from the switch were higher than those without it. As we observe revenues, we can further decompose this restriction on profits into a restriction on the costs of the change. Combining this with a structural model of the industry and variation across markets enables us to relate these restrictions to specific market and competitive factors. Identification derives from observing both switches to a different price positioning and exits. Intuitively, if repositioning costs were zero, a firm whose revenues do not cover fixed costs under its current pricing strategy could costlessly shift to an alternative pricing strategy with higher net payoffs. Observing another firm stay in the market under the alternative pricing strategy reveals that the net payoffs for this alternative are positive. Observing, at the same time, that the focal firm is *exiting*, and not switching, thus indicates that the repositioning costs of switching to the alternative strategy are large.

Additional identification derives from the joint distribution of entry, stays, switches, exits, and revenues observed across markets. The level of present-discounted revenues required to make $\mathcal{N}$ incumbents switch to a pricing strategy versus that required to make $\mathcal{N}$ entrants choose that strategy, identifies the extent to which the repositioning costs are higher than entry costs. The level of present-discounted revenues required to make $\mathcal{N}$ entrants choose a pricing strategy versus required to make $\mathcal{N}$ incumbents who currently operate under that strategy to exit, identifies the extent to which the repositioning costs are sunk.

We then combine this identification strategy with a model of format choice to decompose the effect of repositioning into revenue and cost components. This decomposition is informative to the underlying choice problem. On the revenue side, for example, a move from PROMO to EDLP implies a loss to the supermarket in its price discrimination ability as discussed above, as well as demand losses from potential consumer antagonism to changes in pricing policies (Anderson and Simester (2010)). On the cost side, much of costs associated with advertising the new positioning; with the man-hours involved in updating inventory and supply-chain systems for changing pricing strategy; and with purchase of new pricing and demand-management software to manage promotional activity, are sunk. As the demand-side effects are long-run, and the cost-side investments are sunk, these cost-benefit trade-offs involve dynamic considerations. Further, strategic interaction from other supermarkets are likely important. Most retail markets in the US tend to be concentrated, with a few (3-5) dominant players controlling the market, irrespective of its size (Ellickson (2007)), implying firms face oligopolistic competition at the local market level.

Accommodating these key considerations, we utilize an empirical framework that treats format change as a dynamic problem with sunk investment. Strategic interactions are accommodated by formulating the model as a dynamic game of incomplete information with entry and exit, in the spirit of Ericson and Pakes (1995). Using the identification strategy presented above, we propose new ways to infer the structural parameters of the game by exploiting recently developed methods for two-step estimation of dynamic games (Aguirregabiria and Mira (2007); Arcidiacono and Miller (2012)). We also show how to incorporate revenue information (a continuous outcome) into the estimation procedure in an internally consistent manner, while accounting for the dynamic selection induced by the co-determination of these with the discrete-choices, by extending the methods proposed by Ellickson and Misra (2012) to a dynamic environment. The incorporation of strategic interaction is important to the estimation of repositioning costs. For instance, in a competitive market, a supermarket may be reluctant to switch from PROMO to EDLP because it anticipates that price competition may be toughened if a rival firm, currently doing PROMO, also shifts to EDLP in response to its action. In the absence of this control, the persistence induced on pricing strategy (and observed in the data) by such strategic interaction would be falsely interpreted as due to repositioning costs. This is the main additional complication that arises when measuring switching costs for firms as opposed to consumers. This is accommodated in our framework by allowing firms to form beliefs about the reactions of their rivals, which then influence their choice of pricing formats. In our Markov Perfect equilibrium, beliefs and actions are consistent, and will be functions of the state variables faced by the firm. We are thus able to recover the beliefs of the firms directly from the data for use in estimation, by semiparametrically projecting the observed actions of the firms onto the relevant state vector.

Our results imply the cost and revenue effects of changing pricing formats are large and asymmetric. In particular, for the median store in our data, a change from EDLP to PROMO requires a fixed outlay of about \$2.3M borne over a 4 year horizon. On the other hand, a switch from PROMO to EDLP requires outlays about 6 times as large, providing a clear explanation for why EDLP was never uniformly adopted − it is simply too expensive to be viable in most markets. We also find evidence for significant heterogeneity in these costs across markets, holding out scope for geographic segmentation in a given chain's price positioning strategies. Consistent with existing evidence (cited below), we find overwhelming evidence that PROMO produces higher revenues. For the median store-market, PROMO yields an incremental revenue of about \$6.2M annually relative to EDLP. We also find that the entry of Wal-Mart has large and significant effects on the propensity to switch pricing formats. It also has a disproportionately asymmetric effect on supermarket revenues, with its entry hurting revenues of EDLP stores about twice as much as it does PROMO stores (reducing revenues by \$1.47M compared to \$0.69M annually at the median).

Substantively, empirical evidence on the relative attractiveness of EDLP versus PROMO strategies is scarce. In a study from one retailer, Mulhern and Leone (1990) report sales increased in a switch from EDLP to PROMO. In the strongest evidence available so far, randomized pricing experiments involving the Dominick's stores conducted by the University of Chicago (Hoch, Dreze, and Purk (1994)) find that category by category EDLP is not preferred relative to PROMO (revenues declined when categories, but not stores, were switched from PROMO to EDLP). The literature is still lacking a clear accounting of how these trade-offs change when the long-term economic costs of switching are incorporated. In our data, we find that a switch from EDLP to PROMO increases revenues as well as the probability of store-exits, suggesting that format change cost considerations are qualitatively important to an audit of price positioning strategies.

Our approach is closest in structure to Sweeting (2011), who estimates the dynamic costs radio stations face when changing music formats. Substantively, the question we ask is different as there is no role for consumer pricing in radio (since radio music is free); further, compared to his model, we accommodate new entry and allow incumbent firms to exit, which drives part of the identification. In our model, the margin from staying in the market versus exiting identifies the per-period fixed costs of operation; while the margin from changing a format, conditional on staying in the market, identifies format-switching costs. Our paper is also broadly related to an empirical literature that has documented descriptively the effects of Wal-Mart entry on incumbent firms (e.g. Singh, Hansen, and Blattberg (2006); Basker and Noel (2009); Matsa (2011); Ellickson and Grieco (2011)); to a recent empirical literature in Marketing of applying static discrete games to entry models of supermarket supply (Orhun (2006); Vitorino (2007); Zhu and Singh (2009)); and to an ambitious recent structural literature that has modeled the entry decisions of Wal-Mart as dynamic (but abstracting from strategic interactions; Holmes (2011)), or as jointly determined across geographies (but abstracting from dynamics as in Jia (2008) or Ellickson, Houghton, and Timmins (2010)). Our focus on measuring dynamic switching costs for firms complements the recent literature in Marketing that has considered dynamics induced by consumer-side switching costs for demand (Hartmann and Viard (2008); Goettler and Clay (2011)) and for firm's pricing decisions (Dube, Hitsch, and Rossi (2009)). Our empirical exercise can also be thought of as measuring an adjustment cost of changing pricing *strategy*, and is broadly related to the empirical literature measuring the costs to retailers of changing prices (e.g., Levy, Bergen, Dutta, and Venable (1997); Slade (1998)).

More generally, we emphasize that repositioning is fundamentally a dynamic decision due to both the sunk nature of repositioning investments, and because current repositioning decisions affect future demand and competitive reactions. Hence, repositioning decisions in Marketing and Industrial Organization should formally be thought of as *dynamic games*. Here, we illustrate how viewing product markets through this lens enables us to parsimoniously accommodate these dynamic considerations and to structurally estimate the benefits and costs of repositioning in real market settings.

The paper is organized as follows. Section 2 provides background on the supermarket industry, as it appeared in the late 1990s, describes the dataset, establishes key stylized facts, and details our approach to identification. Section 3 introduces our formal model of retail competition, while section 4 outlines our empirical strategy and econometric assumptions. Section 5 contains our main empirical results, along with a discussion of their broader implications. Section 6 concludes.

2 Industry, Data and Stylized Facts

Our data relates to the 1990s, a period of significant change for the U.S. supermarket industry. Conventional supermarket chains faced intense competition from the rise of new store formats and innovative entrants including Club Stores (like Sam's Club and Costco) and limited assortment chains, (such as Aldi and Save-A-Lot). At the forefront was Wal-Mart, which built its first supercenter (a combination discount store and grocery outlet) in 1988, opened its 200^{th} outlet in 1995, and would operate over 1000 supercenters by 2001. The basis of the competitive threat from entry lay in the perception that limited service, thinner assortments and "every day low pricing" created enormous cost savings and increased credibility with consumers. EDLP, together with a limited product assortment, offered the promise of more predictable demand, reduced inventory and carrying costs, fewer advertising expenses, and lower menu and labor costs. Larger scale was thought to go hand in hand with lower prices. Much of this perception was driven by the success of Wal-Mart alone, which leveraged technical sophistication in IT with buying power to squeeze suppliers and tighten margins, staking out a dominant position in the retailing sector and forging an indelible perception as a low-cost leader. Many of the strategic decisions made by the incumbent supermarket chains were geared toward competition with Wal-Mart. A more detailed discussion of reports in the trade-press regarding supermarket's response to Wal-Mart entry and their choice of EDLP or PROMO in response to that entry is available on request from the authors.

While the impact of Wal-Mart on retail competition is undisputed, many observers assumed that the EDLP format would also come to dominate the supermarket landscape, ignoring both the significant sunk investments in repositioning necessary to implement it and the offsetting benefits of having frequent promotions. While Wal-Mart has continued its growth in the supermarket industry, we now know the EDLP revolution did not come to pass. Our empirical analysis is aimed at understanding why. To do so, we seek to decompose the returns to adopting the EDLP or PROMO format into three components: revenues, operating costs, and repositioning costs. We find that while EDLP pricing provides significant cost savings, it is very expensive to implement (i.e. the repositioning costs are significant). Moreover, it leads to a significant reduction in revenues relative to PROMO pricing.

2.1 Data and Descriptive Results

We now describe our dataset, and present some key stylized facts in the data that pin down switching costs. The data for the supermarket industry are drawn from two primary sources: the Trade Dimensions TDLinx panel database and the 1994 and 1998 frames of the Supermarkets Plus Database. Trade Dimensions continuously 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 consulting firms and food manufacturers for marketing purposes. The supermarket category is defined using 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. For the TDLinx panel, Trade Dimensions collects information on average weekly volume, store size, number of checkouts, and several additional store and chain level characteristics by surveying store managers and cross-validating their responses with each store's principal food broker. We are using the 1994, 1998, and 2002 frames from this panel. The TDLinx dataset does not contain information on pricing format. The information on pricing strategy was obtained from a second dataset, the Supermarkets Plus Database, which was only collected in 1994 and 1998, and contained a more detailed set of characteristics. In particular, managers were asked to choose the pricing strategy that was closest to what their store practices on a general basis: either EDLP, PROMO or HYBRID. EDLP was defined as having "Little reliance on promotional pricing strategies such as temporary price cuts. Prices are consistently low across the board, throughout all food departments." PROMO was defined as making "Heavy use of specials − usually through manufacturer price breaks or special deals." The HYBRID category was included for those stores that practiced a combination of the two, presumably across separate categories or departments. Since we are interested in the adoption of a pure EDLP positioning, we include HYBRID stores in the PROMO category. For additional information on the dataset (including a verification of its correlation with actual price variation using independent scanner data) see Ellickson and Misra (2008).

2.1.1 Markets and Market Structure

While there are several retail channels through which to purchase food for at-home consumption (e.g. supermarkets, mom and pop grocers, specialty markets, convenience stores, club stores) we focus on the supermarket channel exclusively, further narrowing our focus to chain supermarkets operating within 276 designated U.S. Metropolitan Statistical Areas (MSAs). Following Ellickson and Misra (2008), which established that strategic pricing decisions have a strong local component, our unit of observation is a store operating in a local market, taken here to be a zip code.[2] Since we are primarily interested in understanding repositioning choices, which only applies to supermarket firms (as opposed to Wal-Mart), the following summary statistics and descriptive analysis will focus exclusively on this set of firms. Any exceptions are noted explicitly.

Table 1 provides statistics that describe the local markets and firms. Focusing on the first frame of the table, we note that the average market contains about 22 thousand consumers, while the full set ranges in size from unpopulated (i.e. zoned to be purely commercial) to 112 thousand. There is also substantial variation in both ethnic composition and income levels across markets. Frames two and three summarize market structure in the two periods for which we have pricing data. While the average market contains just over 2 stores, some contain as many as 16. About 28% percent of stores in the average market choose EDLP, while the remaining 72% offer PROMO. The typical number of stores and the fraction choosing EDLP are both relatively stable over time. The biggest change observed in the data is the number of markets that either contain a Wal-Mart or face one in their surrounding MSA. Both numbers increased by a factor of 5 over this four year period, reflecting the dramatic roll out of the supercenter format that occurred at this time (the number of supercenters increased from 97 to 487 between 1994 and 1998).

Table 2 provides summary statistics for all chain supermarkets (i.e. excluding Wal-Mart) operating in 1994 and 1998, along with separate statistics for the new entrants in 1998 and the stores

[2] A potential concern is the degree to which price decisions are made locally. This issue is discussed in detail in Ellickson and Misra (2008), who document the rich degree of local variation in pricing strategies chosen by individual chains. While several chains do maintain a consistent focus (e.g. Food Lion, Winn-Dixie), many choose a diverse mixture of pricing formats. Consistent with our store level decision model, this diversity extends to the repositioning choice. Of the 1145 stores that were part of a chain that switched the pricing format of three or more stores, 838 (73%) were owned by chains that did not uniformly switch to a particular focus (i.e. EDLP or PROMO). Notably, the firms that did move in a uniform direction were much smaller on average than those that did not.

that chose to exit in 1994. Again, several interesting patterns emerge. As in Table 1, the share of stores choosing EDLP is relatively stable across periods. Moreover, the stores that exit were no more likely to be offering EDLP than those in the market as a whole (note, however, that these are unconditional means). In contrast, the stores that were opened in 1998 were disproportionately offering EDLP, perhaps reflecting the influence of Wal-Mart, or an overall shift in the optimal pricing policy. We further unpack these distinctions below. Most of the other patterns are intuitive. Sales volume, and both store and chain sizes are all increasing over time, as is the percent of stores operated by vertically integrated firms, reflecting long term trends toward larger suburban formats and greater consolidation. Stores that choose to exit have lower sales, smaller footprints and are operated by smaller chains. Conversely, stores that just entered are bigger, owned by larger, more often vertically integrated chains, and tend to have higher sales volumes.

2.1.2 Key Stylized Facts

The identification of repositioning cost is ultimately driven by the firms that choose to switch. We now provide some preliminary descriptive evidence regarding switching behavior. Table 3 summarizes the set of actions taken by the set of incumbent firms that were in operation in 1994. The first panel presents raw counts, the second shows joint probabilities, and the third provides the switching matrix (conditional on your format in 1994, to what state did you transition in 1998). The first thing to note is that the data contain a lot of switches and a fair number of exits. Both are useful for identification. The switches from EDLP to PROMO (and vice versa) provide the variation necessary to identify switching costs, while the exit choices are instrumental for identifying fixed operating costs (and accounting for continuation values). We make this intuition more precise below. Focusing next on the joint probabilities, we note that, not surprisingly, stores mostly stick with their current pricing format. However, as is apparent from the transition matrix, PROMO exhibits the most state dependence: conditional on choosing PROMO in 1994, 81% of stores stay PROMO in 1998 (95% if you ignore the stores that exit). By contrast, conditional on choosing EDLP in 1994, only 67% of stores stay with it in 1998 (79% if you ignore the exits). This suggests that either the benefits of switching from EDLP to PROMO are high, the costs of doing so are relatively low, or some mixture of the two. Finally, we note that, controlling for the fact that PROMO is the more dominant strategy, exit rates are slightly higher for the EDLP stores.

Tables 4 and 5 split these choice and transition patterns conditional on the presence or absence of Wal-Mart. In particular, we divide our local zip code markets into two groups, those in which Wal-Mart was present in the surrounding MSA in 1994 and those in which it was not, repeating the analysis of Table 3 for these two subgroups. The results are contained in Tables 4 and 5. Several noteworthy patterns emerge. The markets in which Wal-Mart is absent (Table 4) are very similar to the full set of markets (not surprising, since they constitute 90% of the overall total). However, the markets in which Wal-Mart is present are quite distinct (Table 5). In particular, firms in these markets are less likely to stick with PROMO, more likely to stick with EDLP, and, conditional on switching, much more likely to adopt the EDLP format. Wal-Mart also makes firms more likely to exit. Thus, Wal-Mart does appear to be a disruptive presence, and one that pushes its competitors towards EDLP or out of the market entirely. This disruption is key to identification, as it provides a reason for firms to change strategies that were ex ante optimal.

We also examine the format decisions of de novo entrants, those firms that entered between 1994 and 1998. Table 6 contains the counts and proportions of their format decisions for the three sets of markets analyzed above. It is interesting to see the split by Wal-Mart's presence. For the full set of markets, the split is 60/40 in favor of PROMO, revealing an overall trend toward EDLP (recall that the proportion in the 1994 data - for all firms - was 70/30). However, there is again a difference between markets with a Wal-Mart and those without: entrants into markets with a Wal-Mart are 7% more likely to choose EDLP. Some of this is clearly driven by selection (Wal-Mart prefers to enter markets which are amenable to EDLP pricing), but it also reflects the fact that repositioning is costly.

Finally, in Figure 1, we examine how revenues change when switching pricing formats and when Wal-Mart enters the store's local market between 1994-1998. Figure 1 shows the mean revenues (in \$1000s per week) across stores-and-zip-codes in 1998, split by pricing strategy choice and by Wal-Mart's presence. We look for a rough estimate of the effect of switching on revenues conditional on Wal-Mart's entry or absence, using a "difference-in-difference" strategy. We compare the change in revenues between 1994 and 1998 of stores that switched, to the change in revenues of stores that stayed with their old pricing format. This is reported on the right-hand side of Figure 1. The noteworthy aspect is the asymmetry associated with Wal-Mart entry in the revenue impact from switching. We see the effect of switching the pricing format relative to staying is weakly positive and roughly symmetric in markets with no Wal-Mart entry (a gain of roughly \$2K/wk when shifting from EDLP to PROMO, and about \$3K/wk from shifting from PROMO to EDLP). However, in markets with Wal-Mart entry, shifting from EDLP to PROMO is associated with a gain of roughly \$29K/wk, but a shift from PROMO to EDLP is associated with a *loss* of roughly \$11K/wk. While these raw mean comparisons are subject to caveats related to selection, this asymmetry indicates that from a pure revenue perspective, differentiation in pricing policy was a better strategy for incumbent supermarkets to compete with Wal-Mart's EDLP model. In our structural model, we will control for selection in estimating revenue effects.

2.1.3 Descriptive Conditional Policy Functions

To further unpack the dynamics of pricing strategy, we now present several linear probability models characterizing the players' propensity to choose alternative actions. These can be viewed as descriptive analogs of the structural policy functions that comprise firm strategy. Each descriptive regression explains a store's discrete choice as a function of market, rival and own characteristics. We present the coefficients for only a small subset of the included covariates to highlight a few patterns, deferring a full analysis to later.

Column 1 of Table 7 examines a store's decision to switch formats (either from EDLP to PROMO, or vice versa) as a function of six key constructs: whether Wal-Mart is present in the local market, whether Wal-Mart is present in the surrounding MSA, whether the store employed the EDLP format in 1994, the share of rival stores employing the EDLP format in 1994, the number of rival stores, the size of the focal store's chain, and our own measure of strategic "focus". To capture the extent to which chains prefer to concentrate on a single pricing format across stores (e.g. to exploit economies of scale and scope), we defined the variable focus as the squared difference between 0.5 and the share of EDLP for stores operated by the chain *outside* the focal market (implying that larger values correspond to chains that tend to use the same strategy in multiple markets). This is intended to capture the scope economies associated with choosing a consistent pricing strategy. We use this measure in the descriptive regressions, as it is symmetric for share-EDLP or share-PROMO.

Turning to the results in column 1, the presence of Wal-Mart is associated with more switches, and the effect is stronger at the MSA level than the zip code level (perhaps reflecting the small number of zip codes in which Wal-Mart was present in 1994). As was clear from the switching matrices, EDLP stores are more likely to switch to PROMO than vice versa. The share of rival stores offering EDLP in the local market is also associated with more switching, as is a larger number of competing stores (although the latter effect is not statistically significant). Most notably, we find that larger, more focused chains are less likely to switch. This suggests that switching costs may be heterogeneous and, in particular, higher for larger firms and those whose reputation is more closely associated with a single pricing strategy (e.g. Food Lion, HEB).

Column 2 examines the decision to exit. Again, Wal-Mart is an important factor in driving stores to exit. In contrast to the switching patterns, EDLP stores are significantly less likely to exit, suggesting that this format, while expensive to adopt, may offer some additional insulation from competitive pressures. Greater competition is associated with more exit, while large, more focused chains are less likely to exit. Column 3 examines entry by supermarket chains. Not surprisingly, firms are less likely to enter local markets that contain a Wal-Mart, but more likely to enter local markets in MSAs that do have a Wal-Mart. This likely reflects underlying growth patterns, rather than a causal effect (to reflect this, expectations of market growth are incorporated into the full structural model). As expected, the effect of competition is negative, while the share of EDLP incumbents is insignificant. Column 4 examines the decision by incumbents to select the EDLP format, conditional on having decided to enter. The only significant driver here is share EDLP, which is positive (although many of the unreported demographic factors were significant as well). This echoes the patterns of assortative matching documented in Ellickson and Misra (2008), where these patterns persist after accounting for correlated unobservables at the market level. Finally, column 5 examines the entry decision of Wal-Mart. Not surprisingly, Wal-Mart pro-actively targets markets with a large share of EDLP incumbents, and prefers markets that already have a large number of stores (they also tend to enter markets which are closer to their home base of Bentonville, AR and in close proximity to a distribution center, which are two of the unreported controls). The correlation with incumbent store counts likely reflects the fact that Wal-Mart tends to target markets with older, smaller incumbents (which are thus present in larger numbers), rather than a perverse taste for competition.

2.1.4 Identification

The key constructs to be identified are the costs of changing formats, as well as the revenue impact of such changes. We first discuss the revenue side. We observe revenues before and after a change in formats. Hence, the revenue effects are identified directly from these data, conditional on being able to account for selectivity induced by the choice of pricing strategy and survival in the market (i.e. not exiting). Stated differently, revenues are observed only conditional on a chosen pricing strategy, and conditional on being in the market. Thus, we need some source of independent variation that induces firms to switch pricing strategy and stay active, or to exit. As we explained in the introduction and documented above, this variation takes the form of entry by Wal-Mart, a large shock to the profitability of firms that likely causes them to re-evaluate their pricing policy and market positioning. However, an identification concern then is that unobservables that induced firms to exit or to change pricing also caused Wal-Mart to enter (or not). To address this, we need some exogenous source of variation that drives Wal-Mart entry across markets, which can be excluded from firm's pricing strategy or exit decisions. In our framework, this variation is provided by two sets of market-level variables. The first captures the market's radial distance from Bentonville, Arkansas. We follow Holmes (2011), who documents convincingly that Wal-Mart followed a systematic strategy of opening its supercenters close to Bentonville, and then spreading these radially inside out from the center. Controlling for MSA characteristics, the distance to Bentonville is excluded from Supermarket payoffs, and serves as one source of exogenous variation driving Wal-Mart entry. The second variable represents the distance of a market from the nearest McLane distribution center. These are 22 large-scale distribution centers that were operated originally by the McLane company, but acquired in 1990 by Wal-Mart to service its supercenters.[3] In the period from 1990-2003, Wal-Mart rolled out supercenters close to these distribution centers (we see evidence for this in our data). We geocode the latitude and longitude of the distribution centers to calculate the Euclidean distance of each of them to the centroid of each MSA. The locations of the distribution centers were chosen in the 1980s by McLane (to service a pre-existing network of convenience stores), and we treat them as pre-determined in our analysis of the 1994 and 1998 data.

We now explain how we can use the observed switching matrix, exit behavior and revenue data to identify the cost-side of the model. The key distinction is to separate the switching costs of changing pricing strategies from the fixed costs of per-period operation. Conceptually, these are different constructs, as the switching costs are sunk and incurred only at the point of a switch, while the fixed costs are incurred every period. Our switching costs are identified from the margin from changing a pricing format versus staying with the current policy, while the fixed costs affect the propensity to stay with the current pricing policy relative to *exiting*. To see this, let $\upsilon_{\mathcal{E}\to\mathcal{P}}$ denote the present-discounted payoff from switching from EDLP pricing to PROMO, and $\upsilon_{\mathcal{P}\to\mathcal{E}}$ denote the present-discounted payoff from switching from PROMO pricing to EDLP. Analogously $\upsilon_{\mathcal{E}\to\mathcal{E}}$ and $\upsilon_{\mathcal{P}\to\mathcal{P}}$ as the present-discounted payoff from staying with EDLP or PROMO respectively. Let $\upsilon_{\mathcal{E}\to Exit}$ and $\upsilon_{\mathcal{P}\to Exit}$ respectively denote the present-discounted payoff from exiting. We normalize these to zero. These objects can be recognized as the "choice-specific" value functions associated with each of these six actions. For ease of notation, we suppress the dependence of these functions on the state vector.

Let $\mathcal{R}_{\mathcal{E}}$ and $\mathcal{R}_{\mathcal{P}}$ denote the per-period revenues from following EDLP or PROMO respectively. For the purposes of this discussion, assume that these have already been estimated using a selectivity-controlled model from the auxiliary revenue data. Thus, $\mathcal{R}_{\mathcal{E}}$ and $\mathcal{R}_{\mathcal{P}}$ are treated as known. Let the fixed costs incurred per-period when using EDLP or PROMO respectively be $(\mathcal{F}_E, \mathcal{F}_P)$, and let $(\mathcal{C}_{\mathcal{E}\to\mathcal{P}}, \mathcal{C}_{\mathcal{P}\to\mathcal{E}})$ denote the key parameters of interest: the cost of switching from one format to another. Then, we can write the choice-specific values from staying with the current

[3]In May 2003, Berkshire Hathaway acquired McLane Company from Wal-Mart for \$1.45 billion.

strategy as,

$$\upsilon_{\mathcal{E}\to\mathcal{E}} = \mathcal{R}_{\mathcal{E}} + \mathcal{F}_E + 0 + \beta\mathbb{E}\left[\upsilon_{\mathcal{E}}(.)\right]$$
$$\upsilon_{\mathcal{P}\to\mathcal{P}} = \mathcal{R}_{\mathcal{P}} + \mathcal{F}_P + 0 + \beta\mathbb{E}\left[\upsilon_{\mathcal{P}}(.)\right] \tag{1}$$

from switching pricing as,

$$\upsilon_{\mathcal{E}\to\mathcal{P}} = \mathcal{R}_{\mathcal{P}} + \mathcal{F}_P + \mathcal{C}_{\mathcal{E}\to\mathcal{P}} + \beta\mathbb{E}\left[\upsilon_{\mathcal{P}}(.)\right]$$
$$\upsilon_{\mathcal{P}\to\mathcal{E}} = \mathcal{R}_{\mathcal{E}} + \mathcal{F}_E + \mathcal{C}_{\mathcal{P}\to\mathcal{E}} + \beta\mathbb{E}\left[\upsilon_{\mathcal{E}}(.)\right] \tag{2}$$

and from exiting as,

$$\upsilon_{\mathcal{E}\to Exit} = 0; \quad \upsilon_{\mathcal{P}\to Exit} = 0$$

In the above, β represents a (fixed) discount factor for the Supermarkets, $\upsilon_{\mathcal{P}}(.)$ the value function conditional on choosing PROMO, $\upsilon_{\mathcal{E}}(.)$ the value function conditional on choosing EDLP, and the expectation $\mathbb{E}(.)$ is taken with respect to the state vector at the time of making the decision (we have suppressed unobservables, as the argument is not changed if we add additive errors). Following Hotz and Miller (1993), the choice-specific value functions $(\upsilon_{\mathcal{P}\to\mathcal{E}}, \upsilon_{\mathcal{E}\to\mathcal{P}}, \upsilon_{\mathcal{E}\to\mathcal{E}}, \upsilon_{\mathcal{P}\to\mathcal{P}})$ are semi-parametrically identified from the observed probabilities of switching, exiting, and staying with current pricing in the data. Then, we can identify the switching costs as,

$$\mathcal{C}_{\mathcal{E}\to\mathcal{P}} = \upsilon_{\mathcal{E}\to\mathcal{P}} - \upsilon_{\mathcal{P}\to\mathcal{P}} \tag{3}$$

$$\mathcal{C}_{\mathcal{P}\to\mathcal{E}} = \upsilon_{\mathcal{P}\to\mathcal{E}} - \upsilon_{\mathcal{E}\to\mathcal{E}} \tag{4}$$

3 Model

In this section, we describe our structural model of supermarket competition and pricing format choice. There are two types of firms, Wal-Mart and conventional supermarkets (e.g. Kroger, Safeway). Supermarket firms are assumed to compete in local markets, taken here to be zip codes, although we allow for some degree of cross-market competition in the case of Wal-Mart.

Supermarket firms choose whether or not to enter a given market, and if so, what pricing format to adopt, either EDLP or PROMO. We also model the entry decisions of Wal-Mart, but assume that every Wal-Mart is EDLP, consistent with both the data and their stated business model. Once they have entered, a supermarket firm's dynamic decisions include whether to continue offering the same format, switch to the alternative (and pay a switching cost), or exit the market entirely. Wal-Marts neither exit nor change formats. For tractability, we assume that firms make independent entry and format decisions across local markets, but allow for correlation and economies of scale and scope by allowing fixed operating costs to depend on past choices the firm has made outside these local markets.

The dynamic discrete game[4] unfolds in discrete time over an infinite horizon, $t = 1, ..., \infty$. Firms compete in M distinct local geographic markets ($m = 1, .., M$). For ease of notation, we 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. We further assume the existence of two potential supermarket entrants per period, who choose whether or not to enter the market in that period and, if so, what pricing strategy to adopt.[5] If they choose not to enter, they are replaced by new potential entrants in the subsequent period. Wal-Mart may also choose whether to enter the market each period and, if they do enter, they do so in the EDLP format. Let N denote the total number of firms (both Wal-Mart and the supermarkets) making decisions in each market each period. Within N, the set of active firms are called incumbents, and the remaining firms potential entrants. We suppress the distinction between potential entrants and incumbents in the general set-up of our model, but will revisit this when we introduce the empirical framework. Within each market, we index firms by $i \in I = \{1, 2, ..., N\}$. Firm i's choice in period t is given by $d_t^i \in \mathbb{D}_i$, while the actions of its rivals are denoted $d_t^{-i} \equiv \left(d_t^1, \ldots, d_t^{i-1}, d_t^{i+1}, \ldots, d_t^N\right)$. The support of $\mathbb{D}_i$ is discrete, and dependent on firm type. For incumbent firms, d_t^i can take three values, [Exit, do EDLP, or do PROMO]. For potential entrants, d_t^i can take three values, [Stay out of the market,

[4] Surveys of this growing literature are provided by Aguirregabiria, Bajari, Draganska, Ellickson, Einav, Horsky, Misra, Narayanan, Orhun, Reiss, Seim, Singh, Thomadsen, and Zhu (2008) and Ellickson and Misra (2011) in the context of static discrete games and by Aguirregabiria and Mira (2010) and Ackerberg, Benkard, Berry, and Pakes (2005) for dynamics.

[5] A normalization on the number of potential entrants of this sort is standard in the dynamic entry literature, as it is not identified without additional information.

Enter with the EDLP pricing format, or Enter with the PROMO pricing format]. For Wal-Mart, d_t^i can take two values, [Stay out of the market, or Enter with the EDLP pricing format].

Decisions and payoffs depend on a state vector, which describes the current conditions of the market, as well as each firm's operating status and pricing format. Following the standard approach in the dynamic discrete choice literature, we partition the current state vector into two components, one that is commonly observed by everyone (including the econometrician) and one that is privately observed by each firm alone, making this a game of incomplete information. We denote the vector of common state variables x_t, which includes market demographics such as population, and a full description of each player's current condition. The key endogenous state variables included in x_t are each firms' current pricing format and whether they are active at the beginning of each period t.

In addition to the common state vector, each firm *privately* observes a vector $\epsilon_t\left(d_t^i\right)$, which depends on its current choice and can be interpreted as a shock to the per period payoffs associated with making that choice, relative to maintaining the status quo.[6] Once again following standard practice, we make two additional assumptions that (a) the unobserved state variables enter additively into each firm's per period payoff function (*Additive Separability*, *AS*), and (b) that ϵ's are also independently and identically distributed (*iid*) across time and over players, and that conditional on each firm's choice in period t, the ϵ's do not affect the transitions of x (*Conditional Independence with Independent Private Values*, *CI/IPV*). We further assume that ϵ's are distributed Type 1 extreme value (T1EV), with density function $g(\cdot)$.

Given assumption *AS*, the per period (flow) profit of firm i in period t, conditional on the current state, can be decomposed as $\Pi^i\left(x_t, d_t^i, d_t^{-i}\right) + \epsilon_t\left(d_t^i\right)$. The profit function is superscripted by i to reflect the fact that the state variables might impact different firms in distinct ways (e.g. own versus other characteristics). Assuming that firms move simultaneously in each period, let $P\left(d_t^{-i}\,|x_t\right)$ denote the probability that firm i's rivals choose actions d_t^{-i} conditional on x_t. Since ϵ_t^i

[6] This can be interpreted as either a shock to revenues or to costs. We can allow for one, but not both. We will interpret the ε-s as shocks to revenues, which enables us to account for selection on these unobservables when we incorporate revenue data in our estimation procedure.

is iid across firms, $P\left(d_t^{-i}\,|x_t\right)$ can be expressed as follows,

$$P\left(d_t^{-i}\,|x_t\right) = \prod_{j\neq i}^{I} p^j\left(d_t^j|x_t\right) \tag{5}$$

where $p^j\left(d_t^j|x_t\right)$ is player j's conditional choice probability (CCP). Taking the expectation of $\Pi^i\left(x_t, d_t^i, d_t^{-i}\right)$ over d_t^{-i}, firm i's expected current payoff (net of the contribution from its unobserved state variables) is given by,

$$\pi^i\left(x_t, d_t^i\right) = \sum_{d_t^{-i}\in D} P\left(d_t^{-i}\,|x_t\right)\Pi^i\left(x_t, d_t^i, d_t^{-i}\right) \tag{6}$$

which accounts for the simultaneous actions taken by each of its rivals. We assume that state transitions follow a controlled Markov process, $F\left(x_{t+1}\left|x_t, d_t^i, d_t^{-i}\right.\right)$, which we can estimate semi-parametrically from the data as all the elements, $\left(x_{t+1}, x_t, d_t^i, d_t^{-i}\right)$ are directly observed. The transition kernel for the observed state vector is then given by,

$$f^i\left(x_{t+1}\left|x_t, d_t^i\right.\right) = \sum_{d_t^{-i}\in D} P\left(d_t^{-i}\,|x_t\right) F\left(x_{t+1}\left|x_t, d_t^i, d_t^{-i}\right.\right) \tag{7}$$

Given the CI/IPV assumption maintained earlier, the transition kernel for the full state vector is,

$$f^i\left(x_{t+1}, \epsilon_{t+1}^i\left|x_t, d_t^i, \epsilon_t^i\right.\right) = f^i\left(x_{t+1}\left|x_t, d_t^i\right.\right) g(\epsilon_{t+1}^i)$$

We now construct each firm's value function, optimal decision rule (strategy), and the conditions for an MPE. Assuming that firms share a common discount factor β, rational, forward-looking firms will choose actions that maximize expected present discounted profits,

$$\mathbb{E}\left\{\sum_{\tau=t}^{\infty}\beta^{\tau-t}\left[\pi^i\left(x_\tau, d_\tau^i\right) + \epsilon_\tau\left(d_\tau^i\right)\right]|x_t, \epsilon_{i\tau}\right\} \tag{8}$$

where the expectation is over all states and actions, whose solution is given by the value function,

$$V_t^i(x_t, \epsilon_t) = \max_{d_t^i} \left[\pi^i\left(x_t, d_t^i\right) + \epsilon_t + \beta \mathbb{E}\left(V_{t+1}(x_{t+1}, \epsilon_{t+1} | x_t, d_t^i)\right)\right] \tag{9}$$

Following standard arguments from the dynamic discrete games literature (e.g., Aguirregabiria and Mira (2007)), an MPE in this set-up implies the following associated conditional choice probabilities,

$$p^i\left(d_t^i | x_t\right) = \frac{\exp\left(v^i\left(x_t, d_t^i\right)\right)}{\sum_{d_t^i \in \mathbb{D}_i} \exp\left(v^i\left(x_t, d_t^i\right)\right)} \tag{10}$$

where, the *choice-specific* value functions, $v^i\left(x_t, d_t^i\right)$, are defined as,

$$v_t^i(x_t, d_t^i) \equiv \pi^i(x_t, d_t^i) + \beta \int \overline{V}_{t+1}^i(x_{t+1}) f(x_{t+1} | x_t, d_t^i) dx_{t+1} \tag{11}$$

In equation (11) above, the *ex ante* (or integrated) value function, $\overline{V}_t^i(x_t)$, is defined as the continuation value of being in state x_t just before ϵ_t is revealed, and is computed by integrating $V_t^i(x_t, \epsilon_t)$ over ϵ_t, i.e., $\overline{V}_t^i(x_t) \equiv \int V_t^i(x_t, \epsilon_t) g(\epsilon_t) d\epsilon_t$. Given that the ϵ's are distributed T1EV, equation (11) reduces to,

$$v^i\left(x_t, d_t^i\right) = \pi^i\left(x_t, d_t^i\right) + \beta \int \left[v^i\left(x_{t+1}, d_{t+1}^{*i}\right) - \ln\left[p^i\left(d_{t+1}^{*i} | x_{t+1}\right)\right]\right] f^i\left(x_{t+1} | x_t, d_t^i\right) dx_{t+1} + \beta\gamma \tag{12}$$

where, $p^i\left(d_t^i | x_t\right)$ is the implied CCP from equation (10), γ is Euler's constant and d_{t+1}^{*i} represents an *arbitrary* reference choice in period $t+1$ (this reference choice reflects the requirement of a normalization for level; for the full derivation of this representation see Arcidiacono and Ellickson (2011)). Note that by normalizing with respect to exit, which is a terminal state after which no additional decisions are made, the continuation value associated with this reference choice can now be parameterized as a component of the per period payoff function, eliminating the need to solve the dynamic programming (DP) problem when evaluating (12). This simplified representation of the choice specific value function exploits the property of *finite dependence*, originally developed in the context of single agent dynamics by Altug and Miller (1998) and later extended to games by Arcidiacono and Miller (2012). Avoiding the full solution of the DP is useful in our setting, as our underlying state space is very high-dimensional. Alternative methods would either involve artificial discretization of the state space (to allow transition matrices to be inverted) or a parametric approximation to the value or policy functions.[7] The current approach requires neither.

Assuming that firms play stationary Markov strategies, we follow Aguirregabiria and Mira (2007) in representing the associated Markov Perfect Equilibrium in probability space, requiring each firm's best response probability function (10) to accord with their rivals' beliefs (5). While existence of equilibrium follows directly from Brouwer's fixed point theorem (see, e.g., Aguirregabiria and Mira (2007)), uniqueness is unlikely to hold given the inherent non-linearity of the underlying reaction functions. However, our two-step estimation strategy (described below) allows us to condition on the equilibrium that was played in the data, which we will assume is unique. This concludes the discussion of the model set-up.

4 Econometric Assumptions and Empirical Strategy

We now introduce the functional forms and explicit state variables that allow us to take the dynamic game described above to data. Essentially, this involves identifying the exogenous market characteristics that influence profits and specifying a functional form for $\Pi^i(\cdot)$, the deterministic component of the per-period payoff function.

Players Although our model incorporates the endogenous actions (and state variables) of three sets of players (incumbent supermarkets, potential supermarket entrants, and Wal-Mart), the revenue and cost implications of repositioning we are interested in are identified from the actions of incumbent supermarkets. Because we condition on the CCPs of all three classes of players and the structural objective function can be separately factored by type, we are able to recover consistent estimates of the structural parameters of interest without specifying the full structure of the cost and payoff functions for non-incumbents. The CCPs outlining the actions of Wal-Mart and the other entrants will be used to capture the beliefs of incumbent supermarkets. The inference of switching costs will be based on the likelihood of the actions of the incumbents, conditional on these

[7] Another option is to switch to continuous time methods (Arcidiacono, Bayer, Blevins, and Ellickson (2010)).

beliefs. This is useful both for reducing the computational burden of estimation and in allowing us to remain agnostic regarding these additional components of the underlying structure.

Payoffs The per-period profit function of incumbent supermarkets captures the revenues that firms earn in the product market, the fixed costs of operation, and the fixed costs associated with repositioning (for potential entrants, it would also include the sunk cost of entry). Since operating costs are not separately identified from the scrap value of ceasing operation, we normalize the latter to zero. We decompose per-period profits as follows,

$$\Pi^i\left(x_t, d_t^i, d_t^{-i}; \Theta\right) = R^i\left(x_t, d_t^i, d_t^{-i}; \theta_R\right) - C^i\left(x_t, d_t^i; \theta_C\right) \tag{13}$$

separating the revenues accrued in the product market from the costs associated with taking choice d_t^i. The parameters $\Theta = (\theta_R, \theta_C)$ index the revenue and cost functions, respectively. Equation (13) is richer than the latent payoff structures often employed in the empirical entry literature, because it splits per-period payoffs into revenue and cost components. We are able to do this because we *observe* revenue data separately for each supermarket, under their chosen pricing strategy, in each market. The incorporation of the revenue data also serves a useful auxiliary purpose: it enables us to measure all costs in dollars.

Revenues We parameterize the revenue function, $R\left(x_t, d_t^i, d_t^{-i}; \theta_R\right)$ as a rich function of both exogenous demographic variables and endogenous decision variables. To capture the heterogeneity of profits across markets, we interact each component of the latter with a full set of variables comprising the former. The demographic (D_m) variables include population, proportion urban, median household income, median household size, and percent Black and Hispanic. In addition we shift the intercept with store/firm characteristics z_i which include store size and the number of stores in the parent chain. The actual specification can be written as

$$R\left(x_t, d_t^i = a, d_t^{-i}; \theta_R\right) = D_m'\theta_R^{0(a)} + z_i^{R\prime}\theta_R^z + D_m'\theta_R^{1(a)} I\left(\text{WM}_{MSA(m)} = 1\right) \tag{14}$$

$$+ D_m'\theta_R^{2(a)}\bar{a}_{-i}^{EDLP} + D_m'\theta_R^{3(a)} N_{-i} + D_m'\theta_R^{4(a)} F_i\left(a\right) \tag{15}$$

In the above $\bar{a}_{-i}^{EDLP}$ is the share of rival stores choosing the EDLP format; N_{-i} is a count of rival firms; $\text{WM}_{MSA(m)}$ is a dummy for whether or not Wal-Mart operates in the firm's MSA and $F_i(a)$ is reflects the "focus" of the parent chain on the particular pricing strategy measured as a percentage of the chains' stores adopting strategy a.

Costs The cost term, which is treated as latent, is parameterized as follows. We assume that all incumbent firms pay a fixed operating cost each period that depends on their current pricing format. In addition, should they choose to switch formats, they incur an additional, one time repositioning cost. To emphasize the difference between these cost components, we subset the state vector, x_t, into two parts, $x_t \equiv \left(d_{t-1}^i, \widetilde{x}_t\right)$, where d_{t-1}^i is supermarket i's pricing strategy in the previous period (which is part of the state vector), and $\widetilde{x}_t$ is everything in state x_t except d_{t-1}^i. We can express costs for an incumbent that chooses to stay in the market (the second term in equation (13)) as,

$$C^i\left(x_t, d_t^i; \theta_C\right) = FC^i(\widetilde{x}_t, d_t^i; \theta_{FC}) + \mathbb{I}\left(d_t^i \neq d_{t-1}^i\right) RC^i(x_t, d_t^i; \theta_{RC})$$

where $FC^i(\cdot)$ represents fixed operating costs and $RC^i(\cdot)$ represents repositioning costs (which are only relevant when the firm changes pricing formats). The indicator, $\mathbb{I}\left(d_t^i \neq d_{t-1}^i\right)$ ensures that $RC^i(x_t, d_t^i; \theta_{RC})$ is incurred only if the pricing strategy chosen today is different from the one chosen in the previous period. This separation clarifies how the identification of the fixed costs separately from the repositioning costs depends on partitions of the state space. The pricing strategy of an incumbent at the beginning of a period is part of the state vector. The difference in outcomes for incumbents when this state changes in a period versus not helps us learn about repositioning costs separately from fixed costs.

The specification of FC is,

$$\begin{aligned} FC^i(\widetilde{x}_t, d_t^i = a; \theta_{FC}) = {} & D_m' \theta_{FC}^{0(a)} + z_i^{C\prime} \theta_{FC}^z + D_m' \theta_{FC}^{1(a)} I\left(\text{WM}_{MSA(m)} = 1\right) \\ & + D_m' \theta_{FC}^{2(a)} E\left(\bar{a}_{-i}^{EDLP}\right) + D_m' \theta_{FC}^{3(a)} F_i(a) \end{aligned} \tag{16}$$

while RC is defined as,

$$RC^i(x_t, d_t^i = a; \theta_{RC}) = D_m' \theta_{RC}^{(a)} + \theta_{RC}^{WM} I\left(\text{WM}_{MSA(m)} = 1\right) + \theta_{RC}^{ES} E\left(\bar{a}_{-i}^{EDLP}\right) + \theta_{RC}^{F} F_i(a) \tag{17}$$

Finally, incumbent firms that choose to exit receive a scrap value associated with selling their physical assets and residual brand value. Since this is not separately identified from the fixed cost of operation, we normalize this scrap value from exiting to zero. The parameters to be estimated are $(\theta_R, \theta_{FC}, \theta_{RC})$. We now present a three step empirical strategy that delivers estimates of this parameter vector. We first provide a short high-level discussion of our estimation approach, and then delve into the specific details.

4.1 Estimation Approach

Our estimation strategy is built on the approach introduced by Hotz and Miller (1993) in the context of dynamic discrete choice, and later extended to games by Aguirregabiria and Mira (2007), Bajari, Benkard, and Levin (2007), Pakes, Ostrovsky, and Berry (2007), and Pesendorfer and Schmidt-Dengler (2008). This approach is typically applied to discrete-choice outcomes. We extend the approach in this literature to incorporate revenue data (a continuous outcome). The key difficulty to be overcome is that revenues are observed only conditional on the chosen action (staying in the market, and choice of pricing). Hence, inference is subject to a complicated selection problem whereby choices are determined in a dynamic game with strategic interaction. We extend methods introduced in Ellickson and Misra (2012) to accommodate the selection in an internally consistent manner to improve inference in the dynamic game.

Our estimation procedure consists of three steps. In step 1, we obtain consistent estimates of the (non-structural) CCPs using a flexible, semiparametric approach. The transition kernels governing the exogenous state variables (e.g. market characteristics) are also estimated. For these, we use a parametric approach, as they are already structural objects at this point. Both sets of estimates are then used to construct the transitions that govern future states and rival actions, which inform the right hand side of (12). The CCPs are also inverted to construct the choice-specific value functions for each action across firms, markets and states. These objects will be used for estimation of the parameter vector $(\theta_R, \theta_{FC}, \theta_{RC})$ in steps 2 and 3.

In step 2, we use the CCPs obtained from step 1 to create a selection correction term for a revenue regression. The correction serves as a control function. Incorporating the control function then enables us to consistently estimate the revenue parameters θ_R using the revenue data. Given estimates of θ_R, we can construct counterfactual revenue functions that provide the potential revenues to a firm if it chooses any of the available strategies (and *not just the one it was observed to choose in the data*).

In step 3, we make a guess of the cost parameters θ_{FC}, θ_{RC}, and combine these with the counterfactual revenues constructed from step 2, to create predicted choice-specific value functions for each incumbent firm across actions, markets and states. The "observed" choice-specific value functions implied by the data are available from step 1, after inverting the CCPs. We then estimate cost parameters θ_{FC}, θ_{RC} by minimizing the distance between the "observed" choice-specific value functions, and the model-predicted choice-specific value functions. Standard errors that account for the sequential estimation are constructed by block bootstrapping the entire procedure over markets.

Loosely speaking, the parameters indexing $R^i(\cdot)$ can be thought of as being estimated from the revenue data (subject to controls for dynamic selection), and the parameters indexing both $FC^i(\cdot)$ and $RC^i(\cdot)$ as estimated from the firm's dynamic discrete choice over actions. We now present the specific details of the procedure.

4.1.1 Step 1: Estimating CCPs and Transitions

We estimate the CCPs semiparametrically using a second order polynomial approximation in the state variables alongside several additional interactions. The transition density of the exogenous elements of the state vector (i.e. demographics) were constructed using census growth projections, while firm and chain level factors were taken as known (the exact specification of the first-stage, and the full-results are available from the authors on request). Thus at the end of this step, we know the transitions conditional on rival's actions, $F\left(x_{t+1}\left|x_t, d_t^i, d_t^{-i}\right.\right)$, and the CCPs that determine those actions, $p^i\left(d_t^i|x_t\right)$. Further, using equations (5) and (7), we can compute the joint probability of rivals' actions, $P\left(d_t^{-i}\left|x_t\right.\right)$, and the transitions that obtain after integrating them out, $f^i\left(x_{t+1}\left|x_t, d_t^i\right.\right)$.

Finally, we let d_t^1 denote the option to exit. Given $p^i\left(d_t^i|x_t\right)$, we can also invert the CCPs using equation (10) to recover the "observed" choice-specific value functions (relative to exit) as implied by the data for every incumbent firm, action, market and state as,

$$v^i\left(x_t, d_t^i\right) = \ln\left(p^i\left(d_t^i | x_t\right)\right) - \ln\left(p^i\left(d_t^1 | x_t\right)\right) \tag{18}$$

where, implicitly, the value from exiting has been normalized to zero, (i.e., $v^i\left(x_t, d_t^1\right) = 0$ in (10)). These objects are then stored in memory, concluding step 1.

4.1.2 Step 2: Selectivity Corrected Revenue Functions

Next, we construct the model predicted analog of $R^i\left(x_t, d_t^i, d_t^{-i}; \theta_R\right)$. To deal with selectivity, we approximate expected revenues by a flexible function of the states and actions, $R(.)$,

$$R^i\left(x_t, d_t^i, d_t^{-i}; \theta_R\right) = R\left(x_t, d_t^i, d_t^{-i}; \theta_R\right) + \eta_t^i\left(d_t^i\right) + \epsilon_t^i\left(d_t^i\right) \tag{19}$$

Actual revenues, $R^i(.)$, also include two error components: η_t^i representing an *unanticipated* shock to revenues from the firms' perspective, and ϵ_t^i, which is the *same* unobserved state variable that appears in the choice model (and, therefore, the source of the selection problem). The difference between η and ϵ is that η is unobserved to the firm and the econometrician while making decision d_t^i, while ϵ is known to the firm when making decision d_t^i, but unknown to the econometrician. Following Pakes, Porter, Ho, and Ishii (2005), η is an expectation error, while ϵ is a standard random utility shock. The section problem can be articulated as the fact that revenues are co-determined with choices, and therefore, $\mathbb{E}\left[\epsilon_t^i\left(d_t^i\right)|d_t^i\right] \neq 0$. Hence, running the regression (19) will give biased estimates of $R(.)$. However, we can accommodate the selectivity by noting that by construction, $\mathbb{E}\left[\eta_t^i\left(d_t^i\right)|d_t^i\right] = 0$, but that $\mathbb{E}\left[\epsilon_t^i\left(d_t^i\right)|d_t^i\right] = \gamma - \ln p^i\left(d_t^i|x_t\right) \neq 0$, which follows from well-known properties of the Type 1 extreme value distribution. The term, $\gamma - \ln p^i\left(d_t^i|x_t\right)$, is a control function that accommodates the fact that from the econometrician's perspective, unobservables are restricted to lie a particular subspace when the firm is observed to have chosen strategy d_t^i. Letting $R_{it}\left(d_t^i\right)$ denote the observed revenues to supermarket i when choosing strategy d_t^i, we can estimate revenues consistently via the following regression,

$$\tilde{R}\left(x_t, d_t^i, d_t^{-i}; \theta_R\right) = R\left(x_t, d_t^i, d_t^{-i}; \theta_R\right) + \eta_t^i\left(d_t^i\right) \tag{20}$$

in which,

$$\tilde{R}\left(x_t, d_t^i, d_t^{-i}; \theta_R\right) = R_{it}\left(d_t^i\right) - \left[\gamma - \ln p^i\left(d_t^i | x_t\right)\right] \tag{21}$$

is a selectivity corrected revenue construct that adjusts for the fact that we only see revenues for the pricing strategy that was actually chosen. Given consistent estimates of the parameters θ_R that index $R\left(x_t, d_t^i, d_t^{-i}; \theta_R\right)$, we are then able to construct the *predicted* revenues for any choice.[8]

We can now compute the expected revenues from the firms' perspective associated with any choice (i.e. the revenue analog of equation (6)). Suppressing the indexing parameters for brevity, these expected revenues are then given by,

$$r^i\left(x_t, d_t^i\right) = \sum_{d_t^{-i} \in D} P\left(d_t^{-i} | x_t\right) R^i\left(x_t, d_t^i, d_t^{-i}\right) \tag{22}$$

in which the $P\left(d_t^{-i} | x_t\right)$ are already known from step 1. By choosing a functional form that is linear in its parameters for $R^i\left(x_t, d_t^i, d_t^{-i}\right)$, expected revenues (22) can be constructed directly as a linear function of expected actions.

4.1.3 Step 3: Minimum Distance Estimation of Costs

The goal in this step is to estimate the cost parameters, θ_{FC}, θ_{RC}. To understand the approach, recall that we can write the choice specific value function (CSVF) as,

$$v^i\left(x_t, d_t^i\right) = \pi^i\left(x_t, d_t^i\right) + \beta \int \left[v^i\left(x_{t+1}, d_{t+1}^{*i}\right) - \ln\left[p^i\left(d_{t+1}^{*i} | x_{t+1}\right)\right]\right] f^i\left(x_{t+1} | x_t, d_t^i\right) dx_{t+1} + \beta\gamma$$

[8] In general, one should take care in using two-stage approaches with fitted CCPs, particularly in cases with limited data or when the CCPs for the chosen action are naturally small. In such cases, the estimation error can severely effect the quality of the regression results. To check/correct for such bias, we followed an approach outlined in Pakes and Linton (2001) that uses a Taylor-series-based adjustment factor ($\frac{1}{p}$) to mitigate the bias. Since, in our case, the probabilities are reasonably large (with an IQR=$\{0.6, 0.9\}$), the resultant bias appears negligible. Nevertheless, the results reported later are based on this bias-corrected specification. We thank the editor for this suggestion.

In above, d^{*i}_{t+1} is a reference alternative, here chosen as the option to exit in the next period. By choosing to normalize with respect to exit, an action whose continuation value has now been normalized to zero, the first component in the second term of the CSVF drops out (i.e. $v^i\left(x_{t+1}, d^{*i}_{t+1}\right) \equiv 0$). The remaining component of the continuation value can now be constructed directly from the data (using the first-stage CCPs and the structural components of the transition kernel) and treated as an offset term. We construct the empirical analog of this offset term as follows,

$$\varsigma_0^{\ln P}\widehat{\left(x_t, d_t^i\right)} = -\beta \int \ln\left[p^i\left(d^{*i}_{t+1}|x_{t+1}\right)\right] f^i\left(x_{t+1}|x_t, d_t^i\right) dx_{t+1} \tag{23}$$

We can compute the simulated analog of this future value via Monte Carlo simulation. All that remains is the per period payoff function $\pi^i\left(x_t, d_t^i\right)$, which has already been decomposed into its revenue component (constructed from (22)) and the contribution from the cost side. Because the parameters that index the revenue functions have already been recovered from step 2, the expected revenues associated with each format (or exit) choice can now be treated as an additional offset term. We can write the model-predicted CSVF as,

$$v^i\left(x_t, d_t^i; \theta_{FC}, \theta_{RC}\right) = \underbrace{r^i\widehat{\left(x_t, d_t^i\right)} - C^i\left(x_t, d_t^i; \theta_{FC}, \theta_{RC}\right)}_{\pi^i\left(x_t, d_t^i\right)} + \varsigma_0^{\ln P}\widehat{\left(x_t, d_t^i\right)}$$

where $r^i\widehat{\left(x_t, d_t^i\right)}$ is available from step 2, $\varsigma_0^{\ln P}\widehat{\left(x_t, d_t^i\right)}$ is constructed as above, and finally $v^i\left(x_t, d_t^i; \theta_{FC}, \theta_{RC}\right)$ is the predicted CSVF for the current guess of the cost parameters θ_{FC}, θ_{RC}. We can now recover the cost parameters by minimizing the distance between the model-predicted CSVF and the "observed" CSVFs from step 1 (equation 18):

$$\left\| v^i\left(x_t, d_t^i\right) - v^i\left(x_t, d_t^i; \theta_{FC}, \theta_{RC}\right)\right\| \tag{24}$$

A concern with this estimator is that the effective instrument in the resulting estimating equations is $\frac{\partial v^i\left(x_t, d_t^i; \theta_{FC}, \theta_{RC}\right)}{\partial \theta}$, which is then correlated with the "errors",

$$\xi^i\left(x_t, d_t^i; \theta_{FC}, \theta_{RC}\right) = v^i\left(x_t, d_t^i\right) - v^i\left(x_t, d_t^i; \theta_{FC}, \theta_{RC}\right) \tag{25}$$

since the implied estimating equations are implicitly,

$$\sum_i \sum_t \frac{\partial v^i\left(x_t, d_t^i; \theta_{FC}, \theta_{RC}\right)}{\partial \theta} \xi^i\left(x_t, d_t^i; \theta_{FC}, \theta_{RC}\right) = 0 \tag{26}$$

This issue is particularly relevant for the parameters that pertain to endogenous constructs. To address this we use alternative instruments for these estimating equations. In particular, for the parameters related to Wal-Mart and the strategy choices of the supermarkets, we use functions of the variables (z_t) excluded from the focal store's payoffs (e.g., distance to Bentonville and distance to distribution centers for Wal-Mart; and the focus of the chain, store size, and so forth for competing supermarkets), in addition to market demographics (D_m). Denote these functions $h\left(z_t, D_m\right)$.[9] Using these, we then define our estimating equations as,

$$\sum_i \sum_t h\left(z_t, D_m\right) \xi^i\left(x_t, d_t^i; \theta_{FC}, \theta_{RC}\right) = 0 \tag{27}$$

Our cost estimates are then obtained as the $\left(\theta_{FC}^*, \theta_{RC}^*\right)$ that solve these equations in-sample.[10]

5 Results

We now discuss results from the estimation of our structural model. We first discuss the estimates from the revenue side, and then present the cost side results.

5.1 Revenues

We start by documenting the revenue implications of following an EDLP versus PROMO pricing strategy. We obtain the implied revenues as the selection-corrected predictions from the revenue regression model. The full estimates from the revenue regression for both EDLP and PROMO are presented in Tables A1 and A2 in the Appendix. These regressions allow for interactions of each of the variables presented in the first column (named "Variable") with a full range of market-

[9] In our implementation the instrument functions were $h\left(z, D\right) = x$ if the relevant covariate x was exogenous, or equal to a positive function of excluded variables and demographics if not. Details on the actual instruments and functions used are available from the authors.

[10] We thank the Editor for suggesting this estimation approach.

level demographics presented in the second column (named "Interactions"). They also correct for selectivity using the control function approach outlined earlier. Rather than discuss these separately, we present the predicted revenues from this model. We first ask how revenues would look if every supermarket we observe in 1994 chose EDLP. In Figure 2, we plot a histogram of the predicted PROMO revenues (top left panel). Analogously, we then ask how revenues would look if every supermarket we observe in 1994 instead chose EDLP (plotted in top right panel). For what follows, these plots and the numbers below are presented in units of 1000s of \$/week. Comparing the two histograms, we see that revenues are higher under PROMO. To get a sense of the differences in dollar terms, in Table 8, we present the 5th, 50th and 95th percentiles of the distribution of revenues under EDLP and PROMO. Looking first at the 50th percentile, we see the median store-market under PROMO earns revenues of about \$119.72K more per week relative to the median store-market under EDLP. Converting to an annual basis, this difference translates to about \$6.22 Million per year (\$119.72K per week $\times$ 52 weeks). Comparing store-markets at the 5th percentile of the revenue distribution under both formats, this difference is about \$3.68M annually in favor of PROMO (\$70.95K per week $\times$ 52 weeks). At the 95th percentile of the revenue distribution under both formats, this difference is about \$5.37M annually in favor of PROMO (\$103K per week $\times$ 52 weeks). Clearly, stores earn higher revenues under PROMO, whether large or small, whether in large markets or small markets, and across several competitive conditions. However, our estimates also imply significant heterogeneity across both stores and markets in these effects.

In the bottom panel of Figure 2, we plot the distribution across stores of the change in revenues between the pricing strategy chosen by a store in 1998 versus the alternative strategy. This is analogous to checking the Nash conditions in a static model. The bottom left panel shows how much revenues would have changed if stores that switched to PROMO in 1998 had instead stayed with EDLP (i.e., the distribution of $\widehat{R}_{PROMO98} - \widehat{R}_{EDLP98}|\text{switch to}(PROMO98)$). The bottom right panel shows the how much revenues would have changed if a store that switched to EDLP in 1998 had instead stayed with PROMO (i.e., the distribution of $\widehat{R}_{EDLP98} - \widehat{R}_{PROMO98}|\text{switch to}(EDLP98)$). From the left panel, we see that switching to PROMO from EDLP results in an increase in revenues (so the observed switch is revenue enhancing). From the right panel however, we see switching from EDLP to PROMO mostly decreases revenues (so the observed switch is revenue reducing). This is consistent with the difference-in-differences we presented earlier as part of model-free analysis. Also note, the only way that the model can explain the observed switching into EDLP format given these revenue implications is by postulating a cost saving associated with that format. This is a source of identification in the model.

We now discuss the heterogeneity in revenues across markets, and how various factors affect this heterogeneity. Our strategy for summarizing these results is to present histograms of effects across markets, which should be read alongside tables containing the 5th, 50th and 95th percentiles of each across markets. We organize our discussion around four key variables of interest: (a) the revenue implications of Wal-Mart's presence; (b) the effect of local competition; (c) the effect of the similarity of the chosen pricing strategy with that chosen by local competitors; and (d) economies of scale and scope. Recall from our discussion in §4 that we capture these effects by including the following variables: (a) a dummy for whether or not Wal-Mart operates in the firm's MSA (WM$_{MSA}$); (b) the number of rival firms in the market (N_{-i}); (c) the share of rival stores choosing the EDLP format ($\bar{a}_{-i}^{EDLP}$); and (d) the "focus" of the chain measured as a percentage of the chains' stores adopting strategy a ($F_i\,(a = EDLP)$ and analogously $F_i\,(a = PROMO)$). Each of these variables are interacted with a full range of market demographics, and included as right-hand side variables in the revenue regression (see Tables A1 and A2). In Figure 3, we plot the distribution across markets of the total effect of each of these variables on revenues under the EDLP format. For example, the top right panel in Figure 3 contains a histogram of the effect of Wal-Mart on EDLP revenues. Letting m denote a market, this is essentially a histogram of the Wal-Mart effect on EDLP revenues in market m, computed as,

$$
\begin{aligned}
&[\widehat{\theta}_{0R}^{1(EDLP)} + \widehat{\theta}_{1R}^{1(EDLP)}\,(pop_m) + \widehat{\theta}_{2R}^{1(EDLP)}\,(hhsize_m) + \widehat{\theta}_{3R}^{1(EDLP)}\,(\%black_m) \\
&+ \widehat{\theta}_{4R}^{1(EDLP)}\,(\%urban_m) + \widehat{\theta}_{5R}^{1(EDLP)}\,(\%hisp_m) + \widehat{\theta}_{6R}^{1(EDLP)}\,(hinc_m)]
\end{aligned}
$$

where the $\widehat{\theta}_R$s are the estimated coefficients of the interactions of the WM variable with market demographics in the revenue regression for the EDLP format reported in Table A1. The $\widehat{\theta}_R$ parameters correspond to equation (14) in the text. The other histograms in Figure 3 are created analogously for the other variables, N_{-i}, $\bar{a}_{-i}^{EDLP}$, and $F_i\,(EDLP)$. To again get a sense of the heterogeneity, we report the 5th, 50th and 95th percentiles of these distributions in Table 8.

Looking at the Wal-Mart effect in Figure 3 in conjunction with Table 8, we see the presence of Wal-Mart in the same MSA as a supermarket unambiguously reduces revenues. The net effect for the median EDLP store of Wal-Mart's presence is about \$28K per week (\$1.47 Million annually). Note, this is a Wal-Mart effect specifically, and not a competition effect more generally, as the effect of the number of stores has already been controlled for. There is also significant heterogeneity across markets. From Table 8, for the stores in the 5th percentile, the effect of Wal-Mart entry can be as high as \$48K per week (\$2.5 Million per year). These tend to be larger, more isolated markets, in which entry by Wal-Mart tends to result in especially high substitution. The effect of competition from other supermarkets, as captured by the N_{-i} variable, is also negative as expected. At the median, the addition of another supermarket into the local market reduces revenues for an EDLP store by \$9.58K per week (\$0.5M per year). Looking at the effect of the share of other supermarkets in the local area that are also EDLP, we find mixed evidence. In some markets, the effect is negative, suggesting stronger substitution, while in others, the effect is positive. A priori, it is hard to sign this effect. On the one hand, more EDLP stores in the local area clearly implies stronger substitution, and hence, lower revenues. On the other hand, the presence of other chains of the same format may induce stores to tacitly soften price competition, enabling them to jointly sustain higher base prices. This can improve the revenue profile. Without detailed price data, it is hard to drive deeper into these two stories. The main takeaway is that the data reveal that the cross-store substitution effect does not dominate in several markets.

Figure 3 also reveals some evidence for economies of scope and scale on the demand-side. In particular, supermarkets that have a larger proportion of stores outside of the local market doing EDLP, also tend to earn more under EDLP. This effect is fairly large. At the median, the economies add about \$11.1K per week (\$0.5M per year) to revenues. These economies may arise from the fact that large chains may commit to doing EDLP across many markets (i.e. a size effect), or from the fact that doing EDLP across many markets may signal a consistent price image that has spillovers across markets (a scope effect). There is also evidence of fairly large size/scope effects (significant mass in the right tail), presumably reflecting the higher revenues earned by the largest chains.

Figure 4 presents analogous histograms for these effects on revenues under PROMO pricing. It is interesting to compare the numbers for the effects on PROMO revenues to the effects on revenues under EDLP. The effect of having a Wal-Mart in the MSA on revenues under PROMO is also negative as expected, but significantly lower than for EDLP. At the median, the effect is a \$20.5K reduction in PROMO revenues per week (\$1.07M annually). Comparing this to the effect of Wal-Mart presence for EDLP stores, we see Wal-Mart has a 38% larger effect on EDLP supermarket revenues than PROMO (\$1.47M compared to \$1.07M). Clearly, the EDLP positioning of Wal-Mart leads to stronger substitution with other EDLP stores in the local area, than with other PROMO stores. Also interesting is the evidence for scale and scope economies under PROMO, which contributes about \$39.2K per week (\$2.03M annually) in a median store-market. These tend to be somewhat higher than those of EDLP. This is not very surprising, as communicating a coherent and consistent EDLP policy might be more difficult that claiming to have intermittent promotions and sales. We also see that while competition has a negative impact on both formats the prevalence of EDLP competitors tends to hurt PROMO stores more on average.

5.2 Costs

We now discuss the results on the cost-side of the model. We organize the discussion along similar lines to the revenue side, presenting histograms of totals first, and then of individual effects across markets. Complete estimation results are presented in Tables A1 and A2 in the appendix.

Figure 5 presents histograms of the total fixed costs incurred by incumbent supermarkets under EDLP and PROMO. Analogously, Table 9 presents the 5th, 50th and 95th percentiles of these costs distributions. How should we interpret these costs? First, note that the fixed costs are estimated relative to the value of exiting, which has been normalized to zero. A negative fixed cost estimate indicates the scrap value from exit was higher than incurring the fixed cost from continued operation under that particular pricing format. Second, the revenue data are in \$1000s per week. Hence, the fixed costs should be interpreted in the same units. At the same time, the discrete-choice model is estimated for data on two periods (1994 and 1998) that are separated by 4 years. Thus, the one-time switching costs should be thought of as borne over the 4 year window.

Looking at Figure 5 and Table 9, we see the median fixed cost is \$293.75K per week under EDLP (\$15.3M annually), and \$550.2K per week (\$28.6M annually) for PROMO stores. Note, this should not be compared directly to the median revenues reported in Table 8 because the median store-market for the revenue distribution is not the same as the median store-market for the cost distribution.

Table 9 also reports the switching costs estimates. We estimate the median cost of switching from EDLP to PROMO as \$11.1K per week, which works out to be about \$2.3M over a 4 year horizon. We estimate the median cost of switching from PROMO to EDLP to be much larger, \$477.3K per week, which works out to be about \$99.3M over a 4 year horizon. This implies the cost to the median EDLP store of switching to PROMO is about 42 times higher than the cost to the median PROMO store to switch to EDLP. One issue is that the median PROMO store is different from the median EDLP store. To obtain a comparison holding store-type fixed, we also compute for *each store*, the ratio of switching from PROMO to EDLP to the estimated cost of switching from EDLP to PROMO. The mean is 6.3, suggesting the switch from PROMO to EDLP is around 6 times more costly for the average firm in the distribution.

In order to understand the relative comparison of the fixed costs to the switching costs, note the scale of the fixed costs and the switching costs should be expected to be different: the fixed costs are scaled in relation to the revenue from staying relative to exit, while the switching costs are scaled relative to the *present-discounted* revenues from staying relative to exit. This aspect, along with the fact that the model has to rationalize the fact that there are a large number of switches from EDLP to PROMO, but few from PROMO to EDLP, imply large, asymmetric switching costs.

We now explore heterogeneity in fixed and switching costs across stores and markets. Analogous to the revenue results, we report in Figure 6 histograms across markets of the effect of Wal-Mart, the share of competitors doing EDLP, as well as the "EDLP focus" of the supermarket on fixed costs. Also reported is the distribution of estimated costs of switching to EDLP across markets. Figure 7 reports the same constructs for the costs of doing PROMO.

Looking at Figure 6, we find the presence of Wal-Mart in the supermarket's MSA reduces fixed costs of operation for the EDLP format. One interpretation of this result is that the presence of Wal-Mart lowers the costs of marketing an EDLP price positioning in a local market. For instance, the presence of a Wal-Mart drives traffic into the local market, which reduces the costs of doing week by week advertising. Another interpretation is that the entry of Wal-Mart effectively educates consumers in the local market about the value of an EDLP positioning. The trade-press reports anecdotal evidence consistent with this phenomena. For example, when Wegmans (a regional supermarket chain in the northeast) moved from PROMO to EDLP in anticipation of Wal-Mart's entry, they made large investments in advertising and public relations to justify this repositioning to consumers, while also investing in re-educating and retraining their workforce (at stores and warehouses) to be attuned with the new strategy. Please see our unpublished appendix for several more examples documented in the industry tradepress. Finally, Wal-Mart may reduce costs for everyone by putting pressure on suppliers and improving the overall distribution channel. This impact would be felt irrespective of pricing strategy.

We also see the effect of the chain's "focus" is to reduce fixed costs, which is essentially another manifestation of a scope or scale economy on the cost side. The more the chain tends to do EDLP across the US, the lower are its operating costs of running an EDLP supermarket in a local market. This is intuitive and in line with expectations. From Table 9, we see the effect of these scope economies on the cost side are significantly large: at the median of the distribution, the net effect of chain focus on EDLP positioning about \$179.66K per week. We conjecture that EDLP cost savings are directly linked to a widespread adoption of the practice by the chain and this is reflected in this estimate. A broad take-away from these results is that scope economies in retailing operate over both revenues and costs.

Looking at the results on the PROMO side in Figure 7, we see the presence of Wal-Mart in the local MSA tends to increase the fixed costs of doing PROMO. This likely reflects Wal-Mart's overall impact making it relatively more difficult to convincingly communicate the value of PROMO and consequently increasing service, advertising and other costs to help maintain the positioning. The effect of focus is also consistent with the results for PROMO from the revenue side: a strong focus on PROMO across the country leads to some scale or scope economies in local markets, but there is significant heterogeneity in how this plays out across stores.

We can summarize the results of the structural model as follows. Doing PROMO provides higher margins and revenues. At the median, PROMO pricing provides an incremental revenue of about $6.2M relative to EDLP. EDLP does offer lower fixed costs of operation. However, the cost of switching from PROMO to EDLP is estimated to be about 6 times larger than from switching from EDLP to PROMO. Further, competing with Wal-Mart under EDLP lowers revenues by much more than under PROMO. The 1990s were predicted by some as the decade of the EDLP format. These results add to our understanding of why EDLP adoption has been much more limited than predicted.

5.3 Robustness and Simulations

5.3.1 Common Unobservables

We now discuss the robustness of our estimates to the presence of common, market-level unobservables. A potential concern relates to selection issues arising from unobservables common across firms in a market, which might drive firms actions. This is a recurring but hard to solve problem in the entry literature: markets that are more attractive due to an unobserved (to the econometrician) reason attract more firms (or more firms of a particular type) which, when not controlled for, leads to a counter-intuitive finding that firms prefer to enter markets with more competition. To assess if this is an issue, we re-estimate our revenue regressions with market level (MSA) random effects. While we find that these random effects are useful in predicting revenues, the incremental impact on predicted counterfactual revenues is not large. The correlation between the predicted counterfactual revenues from the random effects specification and our chosen specification is above 0.9. The issue with including unobservables into revenues, however, is that it greatly complicates the structure of the dynamic choice problem if these unobservables are included in the players' information sets. Treating these as persistent shocks would make our first-stage CCP estimates inconsistent and this inconsistency would transmit to the remaining stages as well. Given the qualitatively similar results on the revenue front and the econometric issues in treating these shocks as unobserved information, we choose to retain our simpler specification of the revenue functionals.

5.3.2 What if Wal-Mart was everywhere?

Finally, we use our model and estimates to ask how the distribution of pricing formats would look if Wal-Mart expanded significantly across the US. Our goal is to informally verify that at the estimated parameters, the model predicts, consistent with actual evidence, there will not be significant en mass switching by supermarkets into EDLP, as some had predicted in the early 1990s. We simulate a simple counterfactual by assuming the industry state includes the presence of Wal-Mart in all markets. We then forward-simulated the markets from this initial state allowing for entry, exit and strategy changes based on the model estimates. We report the distribution under the steady state.

Our steady state results suggest that adding Wal-Mart to every market starting from the 1998 conditions does push more market participants toward EDLP, but not in an overwhelming way. In particular, the overall effect is of the order of a 18.8% increase in EDLP adoption across the entire U.S. (34.01% of active supermarkets chose to be EDLP in the counterfactual steady state, compared to 28.7% in the data). At the same time, market structure is also pushed towards higher concentration, as exits in the steady state are around 16.67%, versus the 15.4% observed in the data. Overall, the effect of Wal-Mart is to move the share of EDLP higher and to increase the exit rate. The simulations indicate that even when blanketed by Wal-Mart entry, it is unlikely the US market would tip toward EDLP.

6 Conclusions

This paper has made three contributions. First, we draw attention to three salient features of repositioning decisions in Marketing: that they involve long-term consequences, require significant sunk investments, and are dynamic in their impact. We illustrate that positioning decisions can be empirically analyzed as dynamic games to measure structural constructs like firm's repositioning costs. Second, we cast empirical light on an age-old question in the Marketing of CPG goods: the costs and benefits of doing EDLP versus PROMO. Despite the significant interest in this topic, a full accounting of the long-term cost and benefits of these strategies remains lacking in the literature. Our estimates add to the evaluation of either strategy, and also identify the sources of heterogeneity in the relative attractiveness of either across markets. This helps aid our understanding of the economics of the supermarket industry and the determinants of long-run market structure. Third, we illustrate how observed switches combined with auxiliary post-game data (such as revenues, prices and sales) are useful in cleanly articulating the costs and benefits of repositioning in an environment with strategic interaction.

Our modeling approach has limitations, and is based on assumptions that future research might aim at relaxing. In particular, we highlight three potential avenues of improvement. First, the stage game could be extended to accommodate additional structural elements to better understand the source of revenue differences. For example, Beresteanu, Ellickson, and Misra (2007) employ a Bertrand-Nash stage game that allows them to recover price-cost margins and evaluate changes in consumer surplus. While we do not have the appropriate data to afford such a specification here, other researchers might consider this option in the future. Second, we have focused on local market drivers of pricing strategy, but incorporated scale and scope economies to capture dependencies of strategies across markets in a limited way. A significant, but challenging, extension to the current work would be to fully accommodate the joint choice of pricing strategy across markets. This would require the solution of a daunting dynamic network game, which is outside of the scope of our current analysis. Finally, extending our framework to allow for rich layers of persistent unobserved heterogeneity would an important direction forward. This is an active area of frontier econometric research. We intend to address some of these extensions in our future work. We hope our current work spurs further interest in the dynamics of pricing and repositioning in the field.

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Table 1: Demographics and Market Structure

	Mean	Std Dev	Range
Market Demographics			
Population (in 1000s)	22	15.2	[0,112]
Per Capita Income (in $1000s)	33.9	12.8	[0,135]
Median Rent (in $s)	487.7	163.2	[0,1001]
Share Urban	.78	.33	[0,1]
Share Hispanic	.075	.143	[0,.979]
Share Black	.101	.179	[0,.995]
Market Structure (1994)			
All Stores	2.58	1.86	[1,16]
Chain Stores	2.08	1.78	[0,14]
Share EDLP	.282	.367	[0,1]
WalMart in Local Market	.002	.024	[0,1]
WalMart in MSA	.1	.3	[0,1]
Market Structure (1998)			
All Stores	2.57	1.82	[1,14]
Chain Stores	2.02	1.74	[0,13]
Share EDLP	.281	.371	[0,1]
WalMart in Local Market	.009	.061	[0,1]
WalMart in MSA	.466	.499	[0,1]

Table 2: Store Level Characteristics

	All Stores (1994)			Exitors Only		
Store Characteristics (1994)	Mean	Std Dev	Range	Mean	Std Dev	Range
EDLP	.292	.455	[0,1]	.299	.458	[0,1]
Sales Volume (in $1000s per week)	239.2	142.8	[57,615]	166.7	105.7	[57,615]
Size (in 1000s of sq.ft.)	31.4	16.2	[2,99]	25.1	13.2	[3,99]
Stores in Chain	568.4	667.8	[10,2051]	362.8	545.3	[10,2051]
Average Size, Stores in Chain	30.6	10.3	[3,99]	27.1	9.9	[3,97]
Vertical Integration	.652	.476	[0,1]	.599	.490	[0,1]
	All Stores (1998)			**Entrants Only**		
Store Characteristics (1998)						
EDLP	.287	.452	[0,1]	.400	.490	[0,1]
Sales Volume (in $1000s per week)	282.2	161.2	[38,691]	297.4	169.9	[38,691]
Size (in 1000s of sq.ft.)	33.9	16	[2,190]	38.3	18.4	[4,190]
Stores in Chain	701.2	761.7	[1,2316]	703.4	750.1	[1,2316]
Average Size, Stores in Chain	33.05	9.67	[2,110]	32.8	11.1	[4,110]
Vertical Integration	.709	.453	[0,1]	.758	.428	[0,1]

Table 3: Incumbents' Decisions

Counts	PROMO 98	EDLP 98	EXIT
PROMO 94	9314	494	1673
EDLP 94	836	3180	715
Probabilities	PROMO 98	EDLP 98	EXIT
PROMO 94	.575	.030	.103
EDLP 94	.051	.196	.044
Transitions	PROMO 98	EDLP 98	EXIT
PROMO 94	.811	.043	.146
EDLP 94	.177	.672	.151

Table 4: Incumbents' Decisions (Wal-Mart absent)

Counts	PROMO 98	EDLP 98	EXIT
PROMO 94	8452	401	1471
EDLP 94	774	2784	622
Probabilities	PROMO 98	EDLP 98	EXIT
PROMO 94	.583	.028	.101
EDLP 94	.053	.192	.043
Transitions	PROMO 98	EDLP 98	EXIT
PROMO 94	.819	.039	.142
EDLP 94	.185	.666	.149

Table 5: Incumbents' Decisions (Wal-Mart present)

Counts	PROMO 98	EDLP 98	EXIT
PROMO 94	862	93	202
EDLP 94	62	396	93
Probabilities	PROMO 98	EDLP 98	EXIT
PROMO 94	.505	.054	.118
EDLP 94	.036	.232	.054
Transitions	PROMO 98	EDLP 98	EXIT
PROMO 94	.745	.080	.175
EDLP 94	.113	.719	.167

Table 6: Entrants' Decisions

Counts	All Markets	Wal-Mart In	Wal-Mart Out
PROMO 98	1191	644	547
EDLP 98	795	482	313
Probabilities			
PROMO 98	.60	.57	.64
EDLP 98	.40	.43	.36

Table 7: Descriptive Policy Functions

	Dependent Variable				
	P(Switch|X)	P(Exit|X)	P(Enter|X)	P(EDLP|X)	P(Enter|X)
Wal-Mart in local market	.025 (.016)	.027 (.019)	−.141 (.041)	.020 (.104)	
Wal-Mart in MSA	.017 (.006)	.054 (.008)	.035 (.014)	.053 (.039)	
EDLP (this store)	.136 (.008)	−.023 (.008)			
Share of EDLP (in local market)	.010 (.009)	−.002 (.010)	.005 (.008)	.252 (.034)	.021 (.005)
Number of Rival Stores	.0008 (.0016)	.005 (.002)	−.024 (.004)	.009 (.007)	.019 (.003)
Total Own Stores (all markets)	−.0000238 (.000004)	−.000065 (.00004)			
Focus	−.342 (.035)	−.151 (.002)			
	All regressions include additional market, store and chain controls				

Table 8: Distribution of Estimated Revenues

EDLP	**5%**	**50%**	**95%**
Intercept	116.35	273.28	522.26
Walmart	-48.57	-28.32	-4.21
E(Share of Competitors EDLP)	-12.04	0.58	43.22
Number of Competitors	-12.93	-9.58	-2.49
Focus of Chain (EDLP)	-12.98	11.11	73.36
Total Revenues (Fitted)	185.04	364.05	617.14

PROMO	**5%**	**50%**	**95%**
Intercept	115.86	295.48	510.13
Walmart	-35.13	-20.54	-6.39
E(Share of Competitors EDLP)	-15.19	-6.91	3.92
Number of Competitors	-10.06	-5.86	-1.79
Focus of Chain (PROMO)	-12.11	39.22	86.67
Total Revenues (Fitted)	255.93	483.77	720.44

Table 9: Distribution of Estimated Costs

EDLP	**5%**	**50%**	**95%**
Intercept	201.20	349.04	510.47
Walmart	-128.93	-102.75	-84.44
E(Share of Competitors EDLP)	-24.33	-3.65	21.05
Focus of Chain (EDLP)	-226.71	-179.66	-138.66
Total Fixed Costs (for Non-Switchers)	81.12	293.75	465.87
PROMO	**5%**	**50%**	**95%**
Intercept	433.89	538.61	665.55
Walmart	17.17	27.05	35.60
E(Share of Competitors EDLP)	15.65	37.69	61.78
Focus of Chain (PROMO)	-54.01	-7.48	26.90
Total Fixed Costs (for Non-Switchers)	440.83	550.17	677.98
Switching Cost (EDLP to PROMO)	-30.36	11.13	112.13
Switching Cost (PROMO to EDLP)	357.59	477.34	563.36

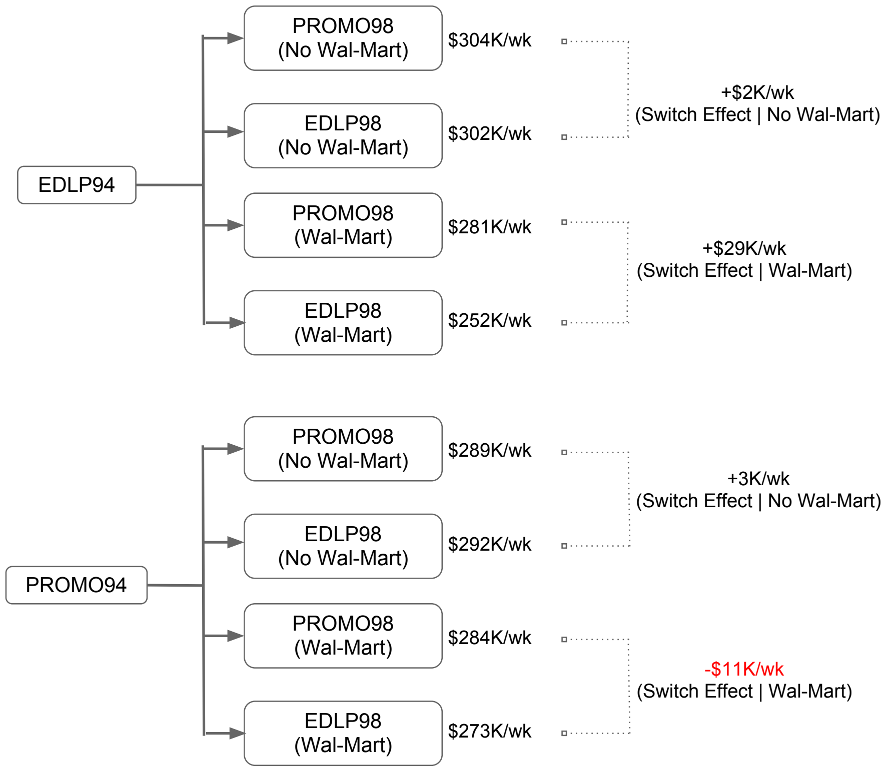

Figure 1: Changes in Revenues by Pricing Format Switch and Wal-Mart Entry

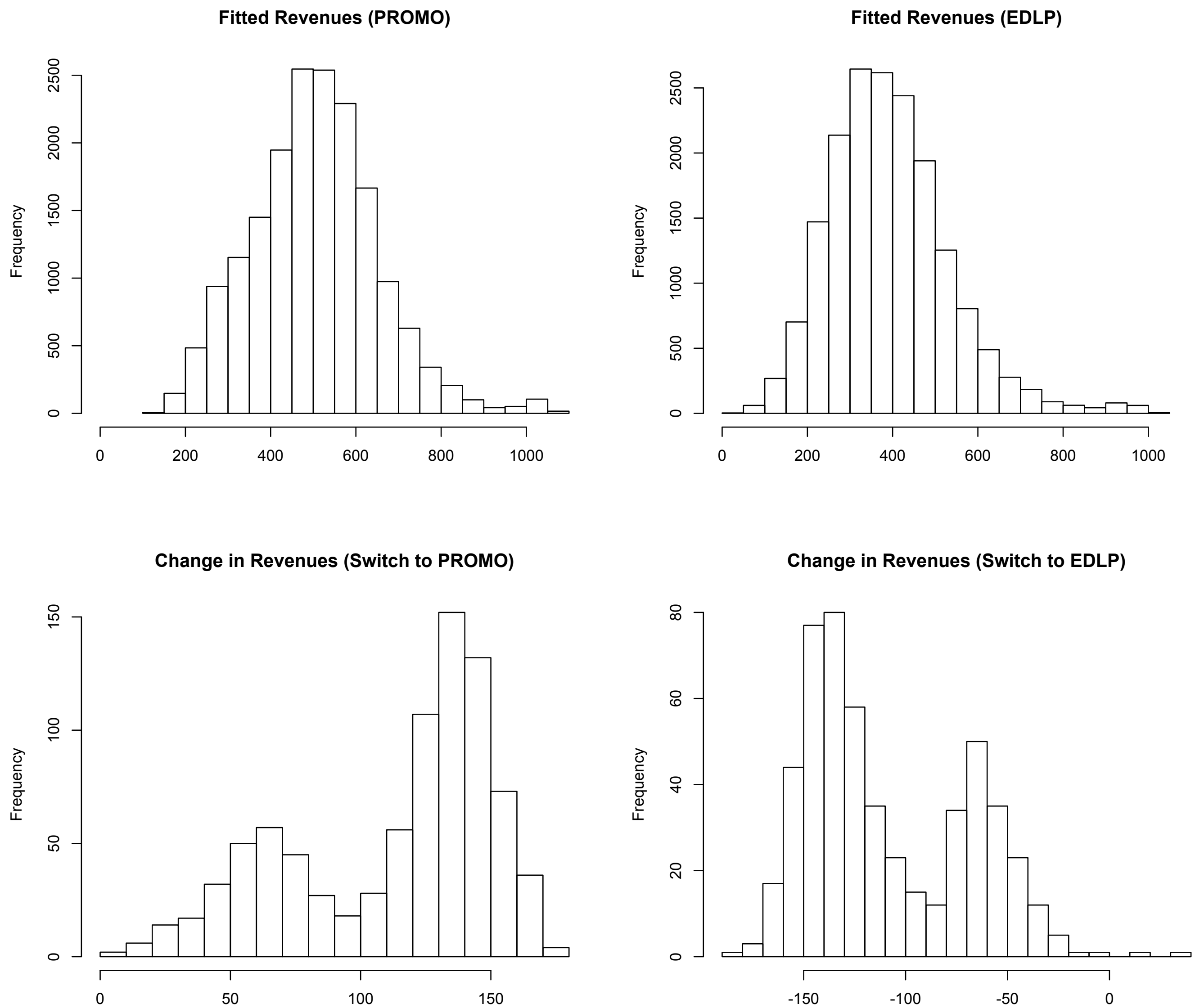

Figure 2: Counterfactual Revenues

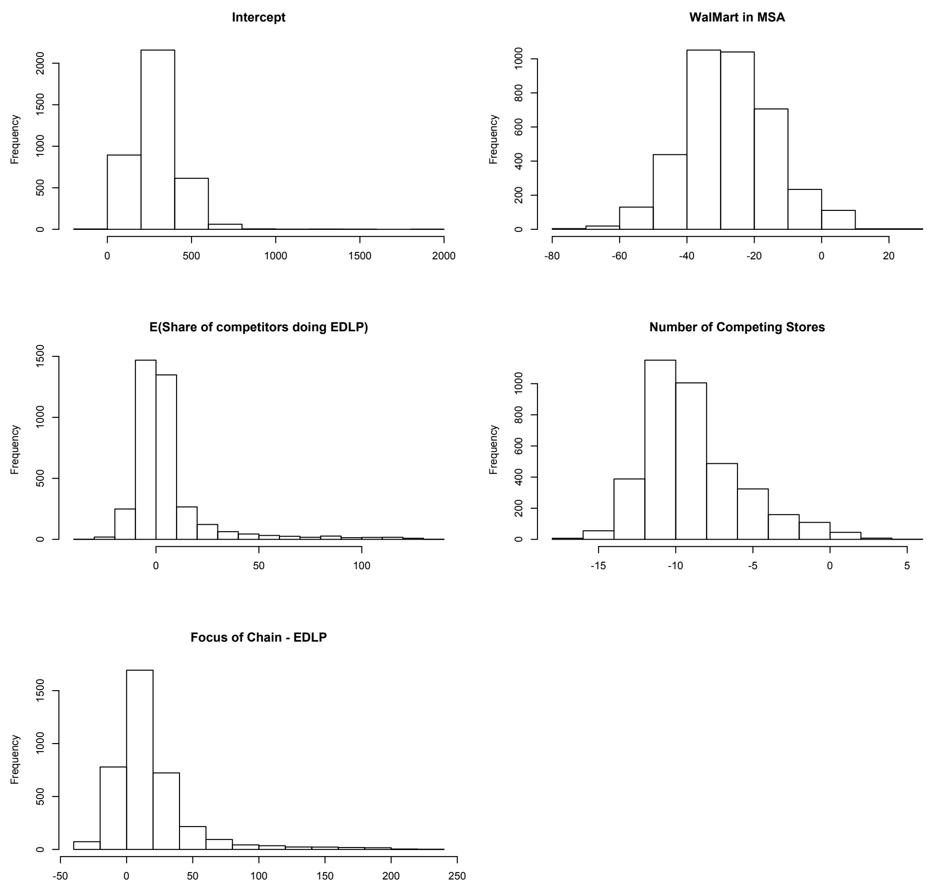

Figure 3: Revenue Components of EDLP

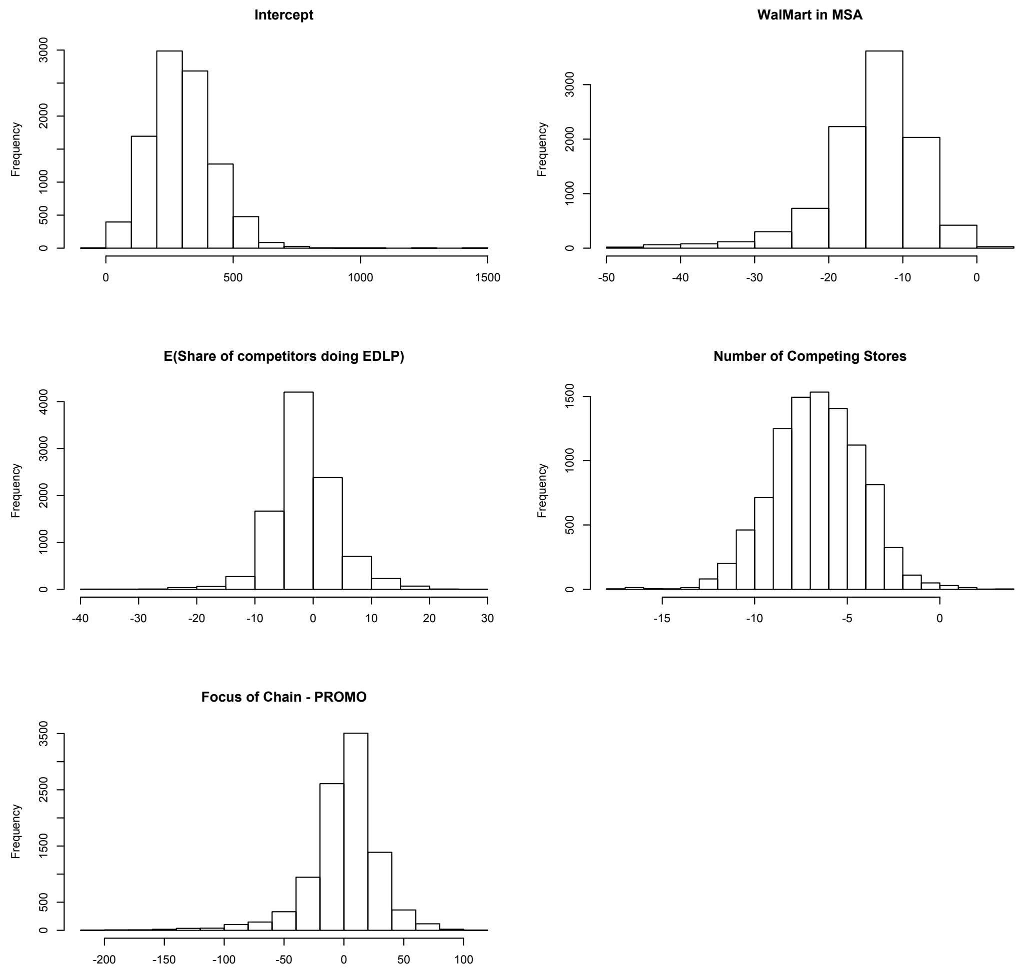

Figure 4: Revenue Components of PROMO

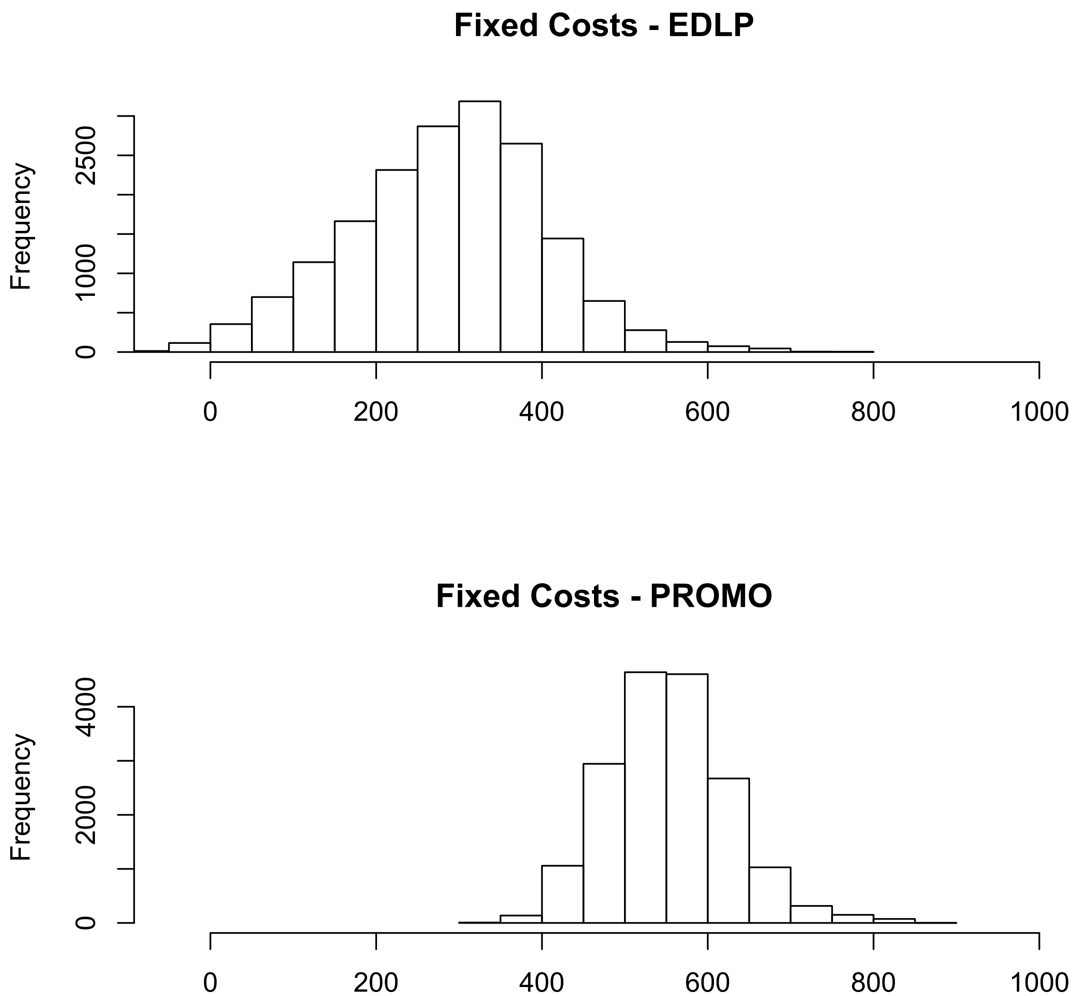

Figure 5: Estimated Fixed Costs

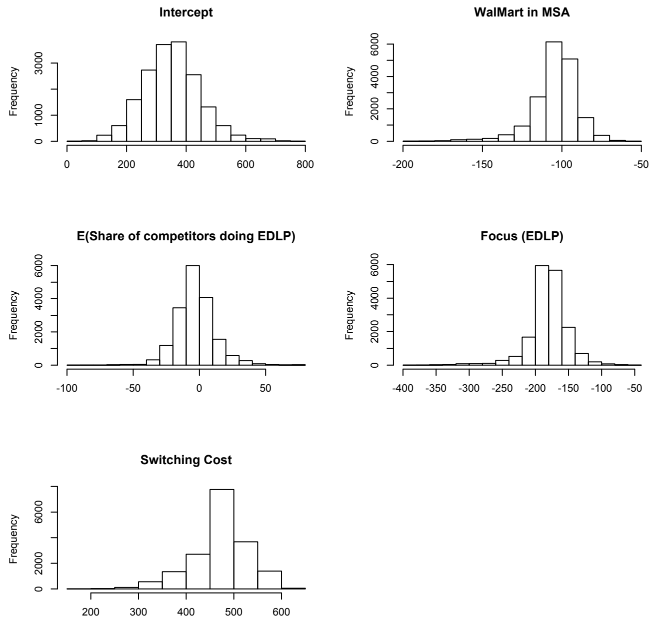

Figure 6: Cost Components of EDLP

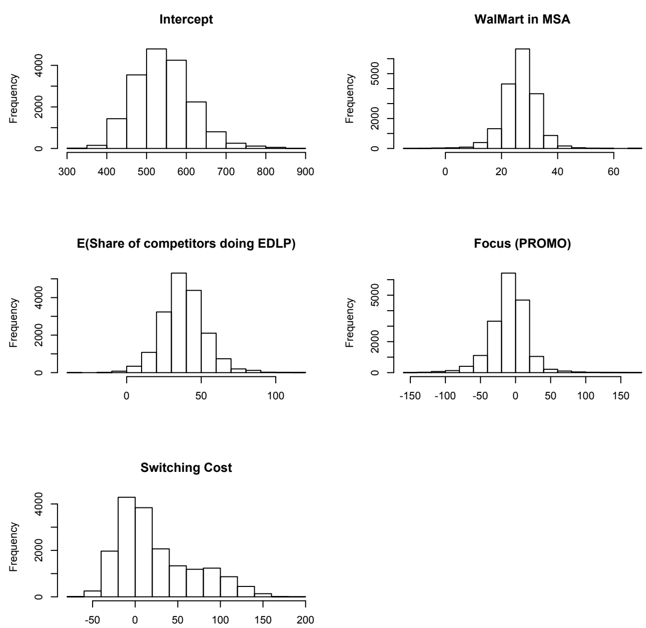

Figure 7: Cost Components of PROMO

					Table A1: Revenue Regression Estimates
			PROMO		**EDLP**
Variable	**Interactions**	**Estimate**	**Std. Error**	**Estimate**	**Std. Error**
Intercept	Constant	-143.4917	38.4107	2.7606	37.6958
	pop	0.0018	0.0003	0.0016	0.0003
	hhsize	29.4688	13.9660	-27.3737	13.8402
	p_black	-42.5423	20.5609	-91.7737	26.1777
	p_urban	38.6491	15.6274	35.6342	15.4588
	p_hisp	86.2794	32.0506	-105.4643	42.4421
	h_inc	0.0019	0.0004	0.0023	0.0004
	size	7.1859	0.1294	7.5947	0.1838
	Tstores	0.0099	0.0012	-0.0021	0.0017
WalMart	Constant	3.4924	18.9370	40.0459	26.8277
	pop	-0.0001	0.0001	0.0000	0.0002
	hhsize	0.1696	7.0774	-9.5970	10.6311
	p_black	-3.0332	12.1695	2.5743	16.0800
	p_urban	-8.0267	8.3187	-32.4061	12.0374
	p_hisp	-36.8025	14.2069	39.5778	29.9141
	h_inc	-0.0001	0.0002	-0.0007	0.0004
E(Comp EDLP)	Constant	45.4532	23.3660	-11.8019	35.9686
	pop	0.0000	0.0002	-0.0005	0.0003
	hhsize	-16.0171	8.4788	6.4146	13.4419
	p_black	18.2148	12.6664	4.5995	19.9579
	p_urban	-15.2756	10.2790	7.1724	11.4828
	p_hisp	21.1111	20.4637	129.1107	32.3871
	h_inc	0.0002	0.0002	-0.0001	0.0005
Focus PROMO/EDLP	Constant	185.2156	42.4260	-120.8199	45.5139
	pop	-0.0006	0.0003	-0.0007	0.0004
	hhsize	-71.4293	15.7550	53.6338	16.7937
	p_black	45.4121	23.8604	12.8066	26.6348
	p_urban	-9.0338	15.8865	27.3170	17.3471
	p_hisp	-43.4603	34.4132	120.7215	38.8835
	h_inc	0.0006	0.0004	-0.0007	0.0006
Number of Competing Stores	Constant	3.4682	4.4740	1.9628	6.2802
	pop	-0.0001	0.0000	0.0000	0.0000
	hhsize	-0.9573	1.3945	-3.8233	2.2772
	p_black	-2.4410	2.2300	15.6963	3.7920
	p_urban	-1.5155	1.9349	-2.4647	2.5457
	p_hisp	8.0419	3.5968	17.2897	8.5114
	h_inc	-0.0001	0.0000	0.0000	0.0001

Table A2: Cost Regression Estimates

		PROMO		EDLP	
Variable	**Interactions**	**Estimate**	**Std. Error**	**Estimate**	**Std. Error**
Intercept	Constant	-40.8906	31.1996	486.5116	29.4313
	pop	0.0004	0.0003	0.0011	0.0003
	hhsize	31.1818	11.6570	-68.7441	10.6749
	p_black	-16.9209	22.1849	18.3064	18.5656
	p_urban	147.9501	12.6642	23.6120	12.8810
	p_hisp	78.3481	28.4861	121.2934	37.5116
	h_inc	0.0023	0.0003	0.0027	0.0003
	size	4.0016	0.0642	3.2505	0.0654
	Tstores	-0.0475	0.0014	-0.0329	0.0012
	VI	5.5494	1.8091	15.8291	1.7537
WalMart	Constant	36.1164	31.2078	71.0421	24.9721
	pop	-0.0005	0.0002	0.0003	0.0002
	hhsize	-7.1406	11.1883	-16.9365	9.0943
	p_black	43.2456	20.1492	2.6052	15.9359
	p_urban	-10.1861	15.9323	-15.6697	10.4204
	p_hisp	-44.8020	31.2732	1.8502	20.3777
	h_inc	0.0002	0.0003	0.0002	0.0003
E(Comp EDLP)	Constant	119.4247	21.2418	100.7033	18.6769
	pop	0.0006	0.0002	0.0008	0.0002
	hhsize	-37.3200	8.2631	-22.6546	6.9649
	p_black	-0.3581	15.4459	25.1018	13.1668
	p_urban	-35.5122	9.5463	-22.2237	7.9338
	p_hisp	77.3049	19.9969	39.6135	17.3118
	h_inc	0.0001	0.0003	-0.0003	0.0002
Focus PROMO/EDLP	Constant	131.8787	36.4711	-223.9241	32.9406
	pop	-0.0002	0.0003	-0.0001	0.0003
	hhsize	-84.0079	13.6877	90.0610	11.8279
	p_black	76.2809	26.7638	-82.3544	21.9314
	p_urban	-10.8516	14.4771	54.7418	13.7870
	p_hisp	0.8312	36.8522	-145.0459	40.7833
	h_inc	0.0010	0.0004	-0.0015	0.0004
Switching Costs	Constant	768.8435	27.2031	146.8000	25.4979
	pop	0.0003	0.0002	-0.0008	0.0002
	hhsize	-63.4806	10.3650	-5.0595	9.6423
	p_black	-149.9769	18.6848	41.1803	17.1722
	p_urban	-18.9121	11.9473	-36.9124	11.0398
	p_hisp	-49.5052	26.1670	52.6532	30.8164
	h_inc	-0.0001	0.0003	0.0006	0.0002
	WalMart in MSA	-107.2976	4.9895	29.7865	4.7857
	E(Comp EDLP)	-17.5035	4.1388	-0.6812	4.5161
	Focus	-114.9448	7.0153	-123.5959	6.8326