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The authors measure the revenue and cost implications to supermarkets of changing their price positioning strategy in oligopolistic downstream retail markets. Their approach formally incorporates the dynamics induced by the repositioning in a model with strategic interaction. They exploit a unique data set 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. The authors exploit the responses of retailers to Wal-Mart entry to infer the cost of changing pricing formats using a revealed-preference argument. The interaction between retailers and Wal-Mart in each market is modeled as a dynamic game. The authors find evidence that entry by Wal-Mart had a significant impact on the costs and incidence of switching pricing strategy. Their results add to the marketing literature on the organization of retail markets and have implications for long-term market structure in the supermarket industry. Their approach, which incorporates long-term dynamic consequences, strategic interaction, and sunk investment costs, may be used to empirically model firms' positioning decisions in marketing more generally.

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

Repositioning Dynamics and Pricing Strategy

Large changes to some or all of a firm's marketing apparatuses 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's Pizza's attempt to change its 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 United States and 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 its downstream distribution strategy, and Procter & Gamble's adoption of value-based pricing in 1992 to reduce trade promotions was a repositioning of the firm's overall pricing strategy (Ailawadi, Lehmann, and Neslin 2001). St-James (2001) describes several instances of repositioning by firms in U.S. consumer product markets, including a detailed history from the 1920s of attempts by Sears Roebuck and Co., Montgomery Wards, and JCPenney chain stores to periodically reposition themselves in response to changing consumer tastes and competition.

Repositioning is different from new entry because 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

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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 has substantive implications for competition and market structure. Low repositioning costs help constrain market power by enabling competitors to react more quickly 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 that current repositioning decisions can affect long-term market outcomes such as the future entry and exit behavior of rival firms. Thus, measuring repositioning costs is important to understanding the economic underpinnings of market structure in an industry.

In this article, 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 (everyday low price) and PROMO (or promotional) strategies.[1] Whereas EDLP stores charge a low regular price per product with little temporal price variation, PROMO stores are characterized by higher regular prices, punctuated by frequent price promotions or sales. A store's choice between EDLP and 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, and valuations (Bell and Hilber 2006; Lal and Rao 1997; Pesendorfer 2002; Salop and Stiglitz 1982; Sobel 1984; Varian 1980). Furthermore, 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 retailers face that affects their price image and has significant long-term implications for profitability and local market structure (Ellickson and Misra 2008; Lal and Rao 1997).

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 cover a census of supermarket entry, exit, revenue, and format choices in the 1990s, include 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 similar to that of Bresnahan and Reiss (1991, 1994): If we observe that a firm switched its price positioning, we conclude 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 other firms 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 N incumbents switch to a pricing strategy compared with that required to make 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 N entrants choose a pricing strategy compared with that required to make 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. For example, on the revenue side, a move from PROMO to EDLP implies a loss to the supermarket in its price discrimination ability, as discussed previously, as well as demand losses from potential consumer antagonism to changes in pricing policies (Anderson and Simester 2010). On the cost side, many of the costs associated with advertising the new positioning, the employee hours involved in updating inventory and supply-chain systems for changing pricing strategy, and purchase of new pricing and demand-management software to manage promotional activity are sunk. Because the demand-side effects are observed in the long run and the cost-side investments are sunk, these cost–benefit tradeoffs involve dynamic considerations. Furthermore, strategic interaction from other supermarkets are likely important. Most retail markets in the United States tend to be concentrated, with a few (three to five) 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 previously, we propose new ways to infer the structural parameters of the game, exploiting recently developed methods for two-step estimation of dynamic

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

games (Aguirregabiria and Mira 2007; Arcidiacono and Miller 2012). In addition, we demonstrate 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 codetermination of these with the discrete choices, by extending the methods that Ellickson and Misra (2012) propose to a dynamic environment. The incorporation of strategic interaction is important to the estimation of repositioning costs. For example, 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 using PROMO, 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 repositioning costs. This is the main additional complication that arises when measuring switching costs for firms rather than 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 (MPE), beliefs and actions are consistent and will be functions of the state variables the firm faces. 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 that 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 approximately \$2.3 million borne over a four-year horizon. In contrast, a switch from PROMO to EDLP requires outlays approximately six 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 research (cited in the following section), we find overwhelming evidence that PROMO produces higher revenues. For the median store market, PROMO yields an incremental revenue of approximately \$6.2 million annually compared with 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 approximately twice as much as it does PROMO stores (reducing revenues by \$1.47 million compared with \$.69 million annually at the median).

Substantively, empirical evidence on the relative attractiveness of EDLP versus PROMO strategies is scarce. In a study of one retailer, Mulhern and Leone (1990) report that sales increased in a switch from EDLP to PROMO. In the strongest evidence available thus far, randomized pricing experiments involving the Dominick's stores conducted by the University of Chicago (Hoch, Drèze, and Purk 1994) find that consumers do not prefer category-by-category EDLP over PROMO (revenues declined when categories, but not stores, were switched from PROMO to EDLP). The literature still lacks 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 in that there is no role for consumer pricing in radio (because radio music is free); furthermore, compared with this 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; in contrast, the margin from changing a format, conditional on staying in the market, identifies format-switching costs. Our article is also broadly related to an empirical literature that has documented descriptively the effects of Wal-Mart entry on incumbent firms (e.g., Basker and Noel 2009; Ellickson and Grieco 2013; Matsa 2011; Singh, Hansen, and Blattberg 2006), to a recent empirical marketing literature applying static discrete games to entry models of supermarket supply (Orhun 2012; Vitorino 2012; 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 Ellickson, Houghton, and Timmins 2010; Jia 2008). Our focus on measuring dynamic switching costs for firms complements the recent marketing literature that has considered dynamics induced by consumer-side switching costs for demand (Goettler and Clay 2011; Hartmann and Viard 2008) and for firm's pricing decisions (Dubé, 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 et al. 1997; Slade 1998).

More generally, we emphasize that repositioning is fundamentally a dynamic decision both because of the sunk nature of repositioning investments and because current repositioning decisions affect future demand and competitive reactions. Thus, 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.

We organize the remainder of the article as follows: The next section provides background on the supermarket industry as it appeared in the late 1990s, describes the data set, establishes key stylized facts, and details our approach to identification. Then, we introduce our formal model of retail competition, followed by an outline of our empirical strategy and econometric assumptions. The next section contains our main empirical results, along with a discussion of their broader implications. We conclude with limitations and suggestions for further research.

INDUSTRY, DATA, AND STYLIZED FACTS

Our data relate 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 (e.g., Sam's Club, Costco) and limited assortment chains (e.g., Aldi, 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 200th outlet in 1995, and would operate more than 1000 supercenters by 2001. The basis of the competitive threat from entry lay in the perception that limited service, thinner assortments, and EDLP created enormous cost savings and increased credibility with consumers. Together with a limited product assortment, EDLP 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 information technology 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 competing with Wal-Mart. (A more detailed discussion of reports in the trade press regarding supermarkets' response to Wal-Mart entry and their choice of EDLP or PROMO in response to that entry is available on request from the authors.)

Although 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, it is now understood that the EDLP revolution did not come to pass. Our empirical analysis is aimed at understanding why. To do so, we 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 expensive to implement (i.e., the repositioning costs are significant). Moreover, it leads to a significant reduction in revenues relative to PROMO pricing.

Data and Descriptive Results

We now describe our data set and present some key stylized facts in the data that pin down switching costs. We drew the data for the supermarket industry 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 United States for use in its 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. Food stores with less than \$2 million in revenues are classified as convenience stores and are not included in the data set. 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 use the 1994, 1998, and 2002 frames from this panel. The TDLinx data set does not contain information on pricing format. We obtained the information on pricing strategy from a second data set, the Supermarkets Plus Database, which was only collected in 1994 and 1998, and contains 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: EDLP, PROMO, or hybrid. The database defines EDLP as having little reliance on promotional pricing strategies such as temporary price cuts. Prices are consistently low across the board, throughout all food departments. The database defined PROMO as the heavy use of specials—usually through manufacturer price breaks or special deals. The hybrid category was included for stores that practiced a combination of the two, presumably across separate categories or departments. Because we are interested in the adoption of a pure EDLP positioning, we include hybrid stores in the PROMO category (for additional information on the data set, including a verification of its correlation with actual price variation using independent scanner data, see Ellickson and Misra 2008).

Markets and market structure. Although 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), who establish 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] Because 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 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 approximately 22,000 consumers, and the full set ranges in size from unpopulated (i.e., zoned to be purely commercial) to 112,000. There is also substantial variation in both ethnic composition and income levels across markets. Frames two and three in Table 1 summarize market structure in the two periods for which we

[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. Although several chains 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 3 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.

Table 1
DEMOGRAPHICS AND MARKET STRUCTURE

	M	*SD*	*Range*
Market Demographics			
Population (in 1000s)	22	15.2	[0, 112]
Per capita income (in $1,000s)	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]
Wal-Mart in local market	.002	.024	[0, 1]
Wal-Mart in MSA	.100	.300	[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]
Wal-Mart in local market	.009	.061	[0, 1]
Wal-Mart in MSA	.466	.499	[0, 1]

have pricing data. While the average market contains just over 2 stores, some contain as many as 16. Approximately 28% of stores in the average market choose EDLP, and 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 five over this four-year period, reflecting the dramatic rollout 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 that chose to exit in 1994. Again, several notable 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 subsequently. Most of the other patterns are intuitive. Sales volume and both store and chain sizes all increase over time, as does the percentage 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 and smaller footprints and are operated by smaller chains. Conversely, stores that just entered are larger; are owned by larger, more often vertically integrated chains; and tend to have higher sales volumes.

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 frame presents raw counts, the second shows joint probabilities, and the third provides the switching matrix (conditional on a store's format in 1994, what state did it transition to in 1998?). First, note that the data contain a great deal 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 in identifying fixed operating costs (and accounting for continuation values). We make this intuition more precise in the following section. Focusing next on

Table 2
STORE-LEVEL CHARACTERISTICS

	All Stores (1994)			*Exitors Only*		
	M	*SD*	*Range*	*M*	*SD*	*Range*
Store Characteristics (1994)						
EDLP	.292	.455	[0, 1]	.299	.458	[0, 1]
Sales volume (in $1,000s per week)	239.2	142.8	[57, 615]	166.7	105.7	[57, 615]
Size (in 1000s of square feet)	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*		
	M	*SD*	*Range*	*M*	*SD*	*Range*
Store Characteristics (1998)						
EDLP	.287	.452	[0, 1]	.400	.490	[1, 0]
Sales volume (in $1,000s per week)	282.2	161.2	[38, 692]	297.4	169.9	[38, 691]
Size (in 1000s of square feet)	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

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

Table 5
INCUMBENTS' DECISIONS (WAL-MART PRESENT)

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

the joint probabilities, we note that, not surprisingly, stores mostly adhere to 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 continued with PROMO in 1998 (95% if we eliminate stores that exit). In contrast, conditional on choosing EDLP in 1994, only 67% of stores adhered to it in 1998 (79% if we eliminate the exits). This suggests that the benefits of switching from EDLP to PROMO are high, the costs of doing so are relatively low, or some mixture of the two is in effect. Finally, we note that, controlling for PROMO being 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. Several noteworthy patterns emerge. The markets in which Wal-Mart is absent (Table 4) are similar to the full set of markets (not surprising, because 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 adhere to PROMO, more likely to adhere to 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, one that pushes its competitors toward EDLP or out of the market entirely. This disruption is key to identification, in that it provides a reason for firms to change strategies that were *ex ante* optimal.

Table 4
INCUMBENTS' DECISIONS (WAL-MART ABSENT)

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

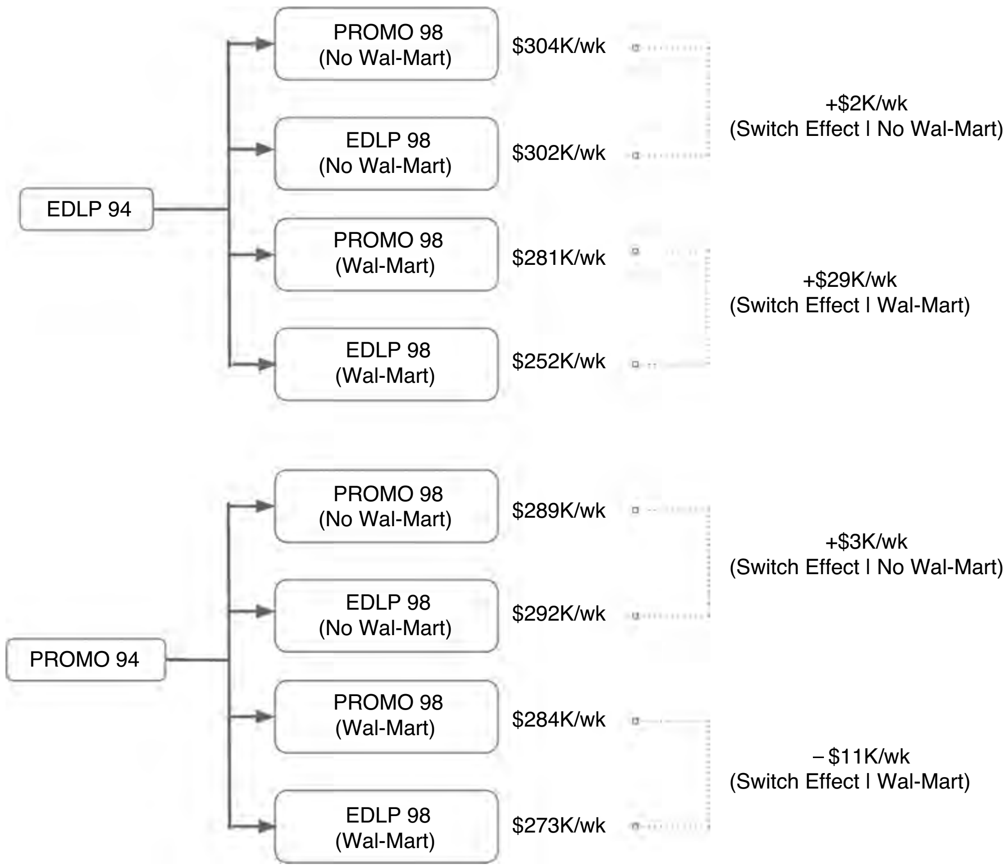
We also examine the format decisions of de novo entrants, those firms that entered between 1994 and 1998. Table 6 contains the counts and proportions of their format decisions for the three sets of markets analyzed previously. Note the difference in the split caused by Wal-Mart's presence. For the full 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 driven by selection (Wal-Mart prefers to enter markets that are amenable to EDLP pricing), but it also reflects 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 and 1998. Figure 1 shows the mean revenues (in thousands of dollars 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 with the change in revenues of stores that stayed with their original pricing format (see the right-hand side of Figure 1). The noteworthy aspect is the asymmetry associated with Wal-Mart entry in the revenue impact from switching. 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 \$2000 per week when shifting from EDLP to PROMO and approximately \$3000 per week 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 \$29,000 per

Table 6
ENTRANTS' DECISIONS

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

Figure 1
CHANGES IN REVENUES BY PRICING FORMAT SWITCH AND BY WAL-MART ENTRY



week, but a shift from PROMO to EDLP is associated with a *loss* of roughly $11,000 per week. Although 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 control for selection in estimating revenue effects.

Descriptive conditional policy functions. To further unpack the dynamics of pricing strategy, we next 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 constitute 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 subsequent sections of the article.

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 seven 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 .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, because 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 at the zip code level (perhaps reflecting the small number of zip codes in which Wal-Mart was present in 1994). As is 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 (though 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

Table 7
DESCRIPTIVE POLICY FUNCTIONS

	Dependent Variable				
	$P(Switch \mid X)$	$P(Exit \mid X)$	$P(Enter \mid X)$	$P(EDLP \mid X)$	$P(Enter \mid X)$
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)			

Notes: All regressions include additional market, store, and chain controls.

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 stores exiting, 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 have a Wal-Mart. This likely reflects underlying growth patterns, rather than a causal effect. (To reflect this, we incorporate expectations of market growth into the full structural model.) As expected, the effect of competition is negative, and the share of EDLP incumbents is insignificant. Column 4 examines the incumbents' decision to select the EDLP format, conditional on having decided to enter. The only significant driver here is share EDLP, which is positive (though many of the unreported demographic factors were significant as well). This echoes the patterns of assortative matching that Ellickson and Misra (2008) document, in which 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 proactively targets markets with a large share of EDLP incumbents and prefers markets that already have a large number of stores. (Wal-Mart also tends to enter markets that are closer to its home base of Bentonville, Ark., and in close proximity to a distribution center, which are two of the unreported controls.) The correlation with incumbent store counts likely reflects 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.

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. Thus, 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 either to switch pricing strategy and stay active or to exit. As we explained and documented previously, this variation takes the form of entry by Wal-Mart, a large shock to the profitability of firms that likely causes them to reevaluate 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 concern, we need some exogenous source of variation that drives Wal-Mart entry across markets, which can be excluded from a 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, AR. 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, we exclude the distance to Bentonville from supermarket payoffs. This 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 were acquired in 1990 by Wal-Mart to service its supercenters.[3] In the period from 1990 to 2003, Wal-Mart rolled out supercenters close to these distribution centers, as is evidenced 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. McLane chose the locations of the distribution centers in the 1980s (to service a preexisting network of convenience stores), and we treat them as predetermined 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, in that the switching costs are sunk

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

and incurred only at the point of a switch, whereas the fixed costs are incurred every period. We identified our switching costs 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 demonstrate this, let $v_{E \to P}$ denote the present-discounted payoff from switching from EDLP pricing to PROMO and $v_{P \to E}$ denote the present-discounted payoff from switching from PROMO pricing to EDLP. Analogously, $v_{E \to E}$ and $v_{P \to P}$ are the present-discounted payoff from staying with EDLP and PROMO, respectively. Let $v_{E \to Exit}$ and $v_{P \to Exit}$ 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 R_E and R_P denote the per-period revenues from following EDLP and 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, we treat R_E and R_P as known. Let the fixed costs incurred per period when using EDLP and PROMO, respectively, be (FC_E, FC_P), and let $(RC_{E \to P}, RC_{P \to E})$ 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 strategy as follows:

$$\begin{aligned} v_{E \to E} &= R_E + FC_E + 0 + \beta \mathbb{E}[v_E(.)] \\ v_{P \to P} &= R_P + FC_P + 0 + \beta \mathbb{E}[v_P(.)], \end{aligned} \tag{1}$$

from switching pricing as

$$\begin{aligned} v_{E \to P} &= R_P + FC_P + RC_{E \to P} + \beta \mathbb{E}[v_P(.)] \\ v_{P \to E} &= R_E + FC_E + RC_{P \to E} + \beta \mathbb{E}[v_E(.)], \end{aligned} \tag{2}$$

and from exiting as

$$v_{E \to Exit} = 0; \quad v_{P \to Exit} = 0.$$

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

$$RC_{E \to P} = v_{E \to P} - v_{P \to P}, \quad \text{and} \tag{3}$$

$$RC_{P \to E} = v_{P \to E} - v_{E \to E}. \tag{4}$$

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, though we allow for some degree of cross-market competition in the case of Wal-Mart. Supermarket firms choose whether 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 its stated business model. After the supermarket firm has entered, its 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 unfolds in discrete time over an infinite horizon, $t = 1, \ldots, \infty$.[4] Firms compete in M distinct local geographic markets ($m = 1, \ldots, M$). For ease of notation, we suppress the market subscript in what follows. For each market–period combination, we observe a set of incumbent firms that are currently active in the market. We further assume the existence of two potential supermarket entrants per period, which choose whether 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 it does enter, it does 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 setup of our model but revisit this when we introduce the empirical framework. Within each market, we index firms by $i \in I = \{1, 2, \ldots, N\}$. 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 $d_t^{-i} \equiv (d_t^i, \ldots, d_t^{i-1}, d_t^{i+1}, \ldots, d_t^N)$. 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, 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

[4]Surveys of this increasing literature stream include Draganska et al. (2008) and Ellickson and Misra (2011) in the context of static discrete games and Aguirregabiria and Mira (2010) and Ackerberg et al. (2005) in the context of dynamics.

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

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 firm's current pricing format and whether it is active at the beginning of each period t.

In addition to the common state vector, each firm privately observes a vector $\epsilon_t(d_t^i)$, 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] Again, following standard practice, we make two additional assumptions: (1) The unobserved state variables enter additively into each firm's per-period payoff function (additive separability), and (2) ϵ are also independently and identically distributed (i.i.d.) across time and over players, and conditional on each firm's choice in period t, ϵ do not affect the transitions of x (conditional independence with independent private values, CI/IPV). We further assume that ϵ 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 $\Pi^i(x_t, d_t^i, d_t^{-i}) + \epsilon_t(d_t^i)$. The profit function is superscripted by i to reflect that the state variables might affect different firms in distinct ways (e.g., own vs. others' characteristics). Assuming that firms move simultaneously in each period, let $P(d_t^{-i} \mid x_t)$ denote the probability that firm i's rivals choose actions d_t^{-i} conditional on x_t. Because ϵ_t^i is i.i.d. across firms, we can express $P(d_t^{-i} \mid x_t)$ as follows:

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

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

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

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

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

Given the assumption of conditional independence with independent private values mentioned previously, the transition kernel for the full state vector is

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

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

Next, we 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:

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

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

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

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

$$p^i(d_t^i \mid x_t) = \frac{\exp[v^i(x_t, d_t^i)]}{\sum_{d_t^i \in \mathbb{D}_i} \exp[v^i(x_t, d_t^i)]}, \tag{10}$$

where the choice-specific value functions, $v^i(x_t, d_t^i)$, are defined as follows:

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

In Equation 11, the *ex ante* (or integrated) value function, $\bar{V}_t^i(x_t)$, 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., $\bar{V}_t^i(x_t) \equiv \int V_t^i(x_t, \epsilon_t) g(\epsilon_t) d\epsilon_t$]. Given that the ϵ are distributed T1EV, Equation 11 reduces to

$$\begin{aligned} v^i(x_t, d_t^i) = {} & \pi^i(x_t, d_t^i) \\ & + \beta \int \{v^i(x_{t+1}, d_{t+1}^{*i}) - \ln[p^i(d_{t+1}^{*i} \mid x_{t+1})]\} \\ & \times f^i(x_{t+1} \mid x_t, d_t^i)\, dx_{t+1} + \beta\gamma, \end{aligned} \tag{12}$$

where $p^i(d_t^i \mid x_t)$ 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 problem when evaluating Equation 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 dynamic programming is useful in our setting because our underlying state space is 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.

[7]Another option is to switch to continuous time methods (Arcidiacono et al. 2010).

Assuming that firms play stationary Markov strategies, we follow Aguirregabiria and Mira (2007) in representing the associated MPE in probability space, requiring each firm's best response probability function (Equation 10) to accord with its rivals' beliefs (Equation 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 nonlinearity of the underlying reaction functions. However, our two-step estimation strategy (described subsequently) enables us to condition on the equilibrium that was played in the data, which we assume is unique. This concludes the discussion of the model setup.

ECONOMETRIC ASSUMPTIONS AND EMPIRICAL STRATEGY

We now introduce the functional forms and explicit state variables that enable us to take the dynamic game described previously 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 nonincumbents. We use the CCPs outlining the actions of Wal-Mart and the other entrants to capture the beliefs of incumbent supermarkets. We base the inference of switching costs on the likelihood of the actions of the incumbents, conditional on these 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.) Because 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:

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

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 its 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, $R(x_t, d_t^i, d_t^{-i}; \theta_R)$ 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 constituting the former. The demographic (D_m) variables include population, proportion urban, median household income, median household size, and percentage 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. We can write the actual specification as follows:

$$\begin{aligned} R(x_t, d_t^i = a, d_t^{-i}; \theta_R) &= D_m'\theta_R^{0(a)} + z_i^{R'}\theta_R^z + D_m'\theta_R^{1(a)} I(WM_{MSA(m)} = 1) \\ &+ D_m'\theta_R^{2(a)}\bar{a}_{-i}^{EDLP} + D_m'\theta_R^{3(a)}N_{-i} + D_m'\theta_R^{4(a)}FO_i(a), \end{aligned} \tag{14}$$

where, $\bar{a}_{-i}^{EDLP}$ is the share of rival stores choosing the EDLP format, N_{-i} is a count of rival firms, $WM_{MSA(m)}$ is a dummy for whether Wal-Mart operates in the firm's MSA, and $FO_i(a)$ reflects the focus of the parent chain on the particular pricing strategy measured as a percentage of the chain's stores adopting strategy a.

Costs

We parameterize the cost term, which we treat as latent, 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, $x_t \equiv (d_{t-1}^i, \tilde{x}_t)$, where d_{t-1}^i is supermarket i's pricing strategy in the previous period (which is part of the state vector), and $\tilde{x}_t$ 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 follows:

$$\begin{aligned} C^i(x_t, d_t^i; \theta_C) &= FC^i(\tilde{x}_t, d_t^i; \theta_{FC}) \\ &+ \mathbb{I}(d_t^i \neq d_{t-1}^i)RC^i(x_t, d_t^i; \theta_{RC}), \end{aligned}$$

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, $\mathbb{I}(d_t^i \neq d_{t-1}^i)$, 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 when it does not provides information about repositioning costs separate from fixed costs. The specification of FC is

$$\text{(15)} \quad FC^i(\tilde{x}_t, d_t^i = a; \theta_{FC}) = D_m'\theta_{FC}^{0(a)} + z_i^{C'}\theta_{FC}^z + D_m'\theta_{FC}^{1(a)} I(WM_{MSA(m)} = 1) + D_m'\theta_{FC}^{2(a)} E(\bar{a}_{-i}^{EDLP}) + D_m'\theta_{FO}^{3(a)} FO_i(a)$$

and RC is defined as

$$\text{(16)} \quad RC^i(x_t, d_t^i = a; \theta_{RC}) = D_m'\theta_{RC}^{(a)} + \theta_{RC}^{WM} I(WM_{MSA(m)} = 1) + \theta_{RC}^{ES} E(\bar{a}_{-i}^{EDLP}) + \theta_{RC}^{FO} FO_i(a).$$

Finally, incumbent firms that choose to exit receive a scrap value associated with selling their physical assets and residual brand value. Because 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 $(\theta_R, \theta_{FC}, \theta_{RC})$. In the next section, we 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.

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 overcome is that revenues are observed only conditional on the chosen action (staying in the market and choice of pricing). Thus, 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 (nonstructural) CCPs using a flexible, semiparametric approach. In addition, we estimate the transition kernels governing the exogenous state variables (e.g., market characteristics). For these transition kernels, we use a parametric approach because they are already structural objects at this point. We then use both sets of estimates to construct the transitions that govern future states and rival actions, which inform the right-hand side of Equation 12. We also invert the CCPs to construct the choice-specific value functions for each action across firms, markets, and states. We use these objects 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 we 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. We construct standard errors that account for the sequential estimation 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. Next, we present the specific details of the procedure.

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. We constructed the transition density of the exogenous elements of the state vector (i.e., demographics) using census growth projections, we took firm- and chain-level factors as known. (The exact specification of the first stage and the full results are available on request.) Thus, at the end of this step, we know the transitions conditional on rival's actions, $F(x_{t+1} \mid x_t, d_t^i, d_t^{-i})$, and the CCPs that determine those actions, $p^i(d_t^i \mid x_t)$. Furthermore, using Equations 5 and 7, we can compute the joint probability of rivals' actions, $P(d_t^{-i} \mid x_t)$, and the transitions that occur after integrating them out, $f^i(x_{t+1} \mid x_t, d_t^i)$.

Finally, we let d_t^1 denote the option to exit. Given $p^i(d_t^i \mid x_t)$, 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

$$\text{(17)} \quad v^i(x_t, d_t^i) = \ln\left[p^i(d_t^i \mid x_t)\right] - \ln\left[p^i(d_t^1 \mid x_t)\right],$$

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

Step 2: Selectivity corrected revenue functions. Next, we construct the model-predicted analog of $R^i(x_t, d_t^i, d_t^{-i}; \theta_R)$. To deal with selectivity, we approximate expected revenues by a flexible function of the states and actions, $R(\cdot)$:

$$\text{(18)} \quad R^i(x_t, d_t^i, d_t^{-i}; \theta_R) = R(x_t, d_t^i, d_t^{-i}; \theta_R) + \eta_t^i(d_t^i) + \epsilon_t^i(d_t^i).$$

Actual revenues, $R^i(\cdot)$, also include two error components: η_t^i, representing an unanticipated shock to revenues from the firm's 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, whereas ϵ is known to the firm when making decision d_t^i but is unknown to the econometrician. In the line with Pakes et al. (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 codetermined with choices, and therefore, $\mathbb{E}[\epsilon_t^i(d_t^i) \mid d_t^i] \neq 0$. Thus, running the regression (Equation 18) will give biased estimates of $R(\cdot)$. However, we can accommodate the selectivity by noting that by construction, $\mathbb{E}[\eta_t^i(d_t^i) \mid d_t^i] = 0$, but that $\mathbb{E}[\epsilon_t^i(d_t^i) \mid d_t^i] = \gamma - \ln p^i(d_t^i \mid x_t) \neq 0$; which follows from well-known properties of the T1EV distribution. The term $\gamma - \ln p^i(d_t^i \mid x_t)$ is a control function that accommodates the fact that from the econometrician's perspective, unobservables are restricted to lie in a particular subspace when the firm is observed to have chosen strategy d_t^i. Letting $R_{it}(d_t^i)$ denote the observed revenues to supermarket i when choosing strategy d_t^i, we can estimate revenues consistently with the following regression:

$$(19)\qquad \tilde{R}(x_t, d_t^i, d_t^{-i}; \theta_R) = R(x_t, d_t^i, d_t^{-i}; \theta_R) + \eta_t^i(d_t^i),$$

in which

$$(20)\qquad \tilde{R}(x_t, d_t^i, d_t^{-i}; \theta_R) = R_{it}(d_t^i) - \left[\gamma - \ln p^i(d_t^i \mid x_t)\right]$$

is a selectivity corrected revenue construct that adjusts for the restriction that we only observe revenues for the pricing strategy that was actually chosen. Given consistent estimates of the parameters θ_R that index $R(x_t, d_t^i, d_t^{-i}; \theta_R)$, 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

$$(21)\qquad r^i(x_t, d_t^i) = \sum_{d_t^{-i} \in D} P(d_t^{-i} \mid x_t) R^i(x_t, d_t^i, d_t^{-i}),$$

in which the $P(d_t^{-i} \mid x_t)$ are already known from Step 1. By choosing a functional form that is linear in its parameters for $R^i(x_t, d_t^i, d_t^{-i})$, expected revenues (Equation 21) can be constructed directly as a linear function of expected actions.

Step 3: Minimum distance estimation of costs. The goal of Step 3 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 follows:

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

In the preceding equation, d_{t+1}^{*i} is a reference alternative, here chosen as the option to exit in the next period. Choosing to normalize with respect to exit, an action whose continuation value has now been normalized to zero, allows the first component in the second term of the CSVF to drop out (i.e., $v^i(x_{t+1}, d_{t+1}^{*i}) \equiv 0$). 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:

$$(22)\qquad \widehat{s_0^{\ln P}(x_t, d_t^i)} = -\beta \int \ln\left[p^i(d_{t+1}^{*i} \mid x_{t+1})\right] \times f^i(x_{t+1} \mid x_t, d_t^i)\, dx_{t+1}.$$

We can compute the simulated analog of this future value using Monte Carlo simulation. All that remains is the per-period payoff function $\pi^i(x_t, d_t^i)$, which has already been decomposed into its revenue component (constructed from Equation 21) 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 follows:

$$v^i(x_t, d_t^i; \theta_{FC}, \theta_{RC}) = \underbrace{\widehat{r^i(x_t, d_t^i)} - C^i(x_t, d_t^i; \theta_{FC}, \theta_{RC})}_{\pi^i(x_t, d_t^i)} + \widehat{s_0^{\ln P}(x_t, d_t^i)},$$

where $\widehat{r^i(x_t, d_t^i)}$ is available from Step 2, $\widehat{s_0^{\ln P}(x_t, d_t^i)}$ is constructed as mentioned previously, and, finally, $v^i(x_t, d_t^i; \theta_{FC}, \theta_{RC})$ 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 17):

$$(23)\qquad \left\| v^i(x_t, d_t^i) - v^i(x_t, d_t^i; \theta_{FC}, \theta_{RC}) \right\|.$$

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

$$(24)\quad \xi^i(x_t, d_t^i; \theta_{FC}, \theta_{RC}) = v^i(x_t, d_t^i) - v^i(x_t, d_t^i; \theta_{FC}, \theta_{RC}),$$

because the implied estimating equations are implicitly

$$(25)\qquad \sum_i \sum_t \frac{\partial v^i(x_t, d_t^i; \theta_{FC}, \theta_{RC})}{\partial\theta} \xi^i(x_t, d_t^i; \theta_{FC}, \theta_{RC}) = 0.$$

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; the focus of the chain, store size, and so forth for competing supermarkets), in addition to market demographics (D_m). Denote these functions $h(z_t, D_m)$.[9]

[8]In general, researchers 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 affect the quality of the regression results. To check and correct for such bias, we followed an approach outlined in Pakes and Linton (2001) that uses a Taylor-series-based adjustment factor (1/p) to mitigate the bias. Because, in our case, the probabilities are reasonably large (with an IQR = {.6, .9}), the resultant bias appears negligible. Nevertheless, the results reported subsequently are based on this bias-corrected specification. We thank the editor for this suggestion.

[9]In our implementation, the instrument functions were h(z, D) = 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 on request.

Using these functions, we then define our estimating equations as follows:

$$\sum_i \sum_t h(z_t, D_m)\xi^i(x_t, d_t^i; \theta_{FC}, \theta_{RC}) = 0. \tag{26}$$

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

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.

Revenues

We begin 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. Appendixes A and B present the full estimates from the revenue regression for both EDLP and PROMO. These regressions allow for interactions of each of the variables presented in the first column (named "Variable"), with a full range of market-level demographics presented in the second column (named "Interactions"), and also correct for selectivity using the control function approach outlined previously. Rather than discuss them separately, we present the predicted revenues from this model. We first ask how revenues would appear if every supermarket we observe in 1994 chose EDLP. In Figure 2, we plot a histogram of the predicted EDLP revenues (top-right panel). Analogously, we then ask how revenues would appear if every supermarket we observe in 1994 instead chose PROMO (plotted in top-left panel). For what follows, these plots and the numbers below are presented in units of 1000s of dollars per week. Comparing the two histograms, we observe that revenues are higher under PROMO. To demonstrate 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. Observing first at the 50th percentile, note that the median store market under PROMO earns revenues of approximately \$119,720 more per week relative to the median store market under EDLP. Converting to an annual basis, this difference translates to approximately \$6.22 million per year (\$119,720 per week × 52 weeks). Comparing store markets at the 5th percentile of the revenue distribution under both formats, we find that this difference is

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

Figure 2
COUNTERFACTUAL REVENUES

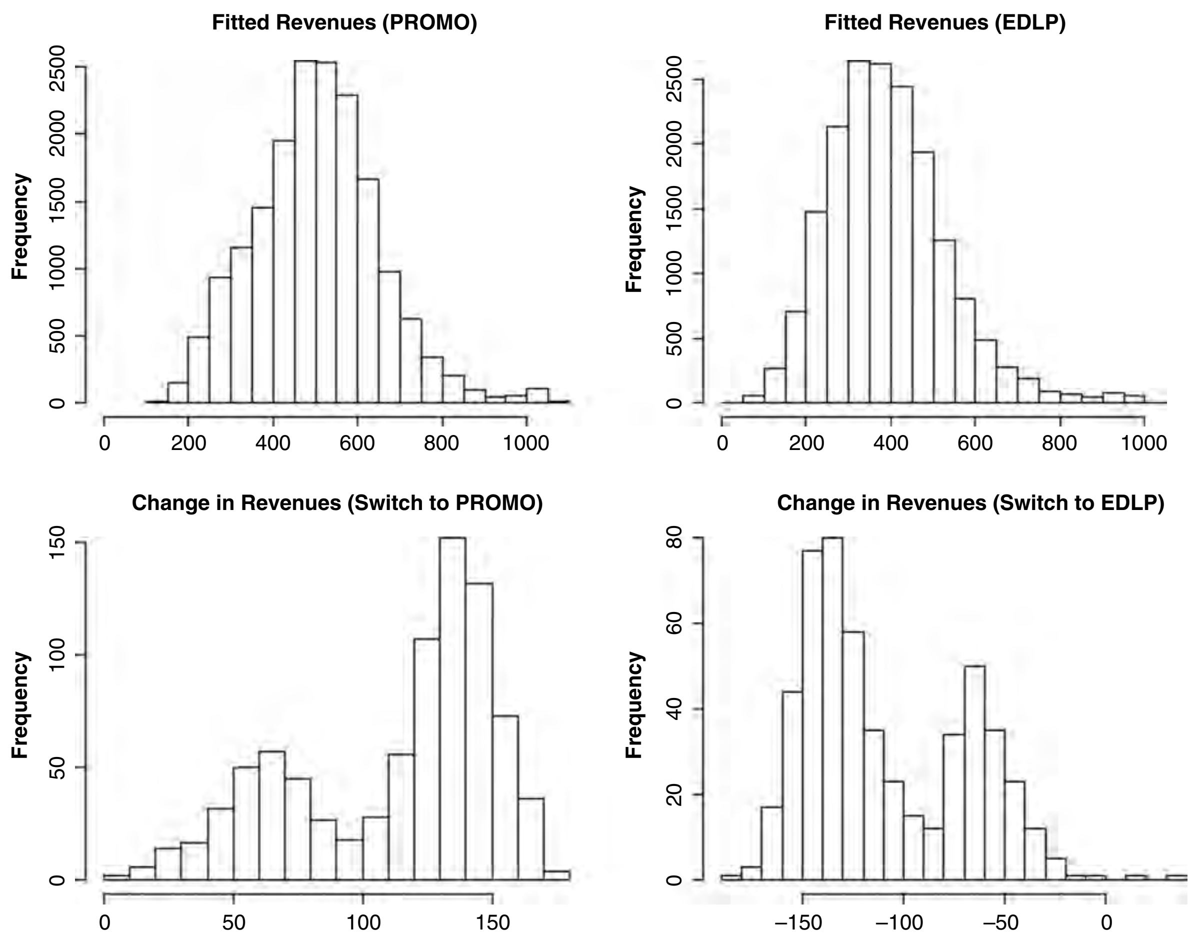


Table 8
DISTRIBUTION OF ESTIMATED REVENUES

	5%	50%	95%
EDLP			
Intercept	116.35	273.28	522.26
Wal-Mart	−48.57	−28.32	−4.21
E(Share of competitors EDLP)	−12.04	.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			
Intercept	115.86	295.48	510.13
Wal-Mart	−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

approximately \$3.68 million annually in favor of PROMO (\$70,950 per week × 52 weeks). At the 95th percentile of the revenue distribution under both formats, this difference is approximately \$5.37 million annually in favor of PROMO (\$103,000 per week × 52 weeks). It is evident that 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 panels 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 $\hat{R}_{PROMO98} - \hat{R}_{EDLP98} \mid$ switch to [PROMO98]). The bottom-right panel shows 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 $\hat{R}_{EDLP98} - \hat{R}_{PROMO98} \mid$ switch to [EDLP98]). From the left panel, it is evident that switching to PROMO from EDLP results in an increase in revenues (so the observed switch is revenue enhancing). However, the right panel, indicates that switching to EDLP from PROMO mostly decreases revenues (so the observed switch is revenue reducing). This is consistent with the difference-in-differences approach we presented previously as part of model-free analysis. The only way 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.

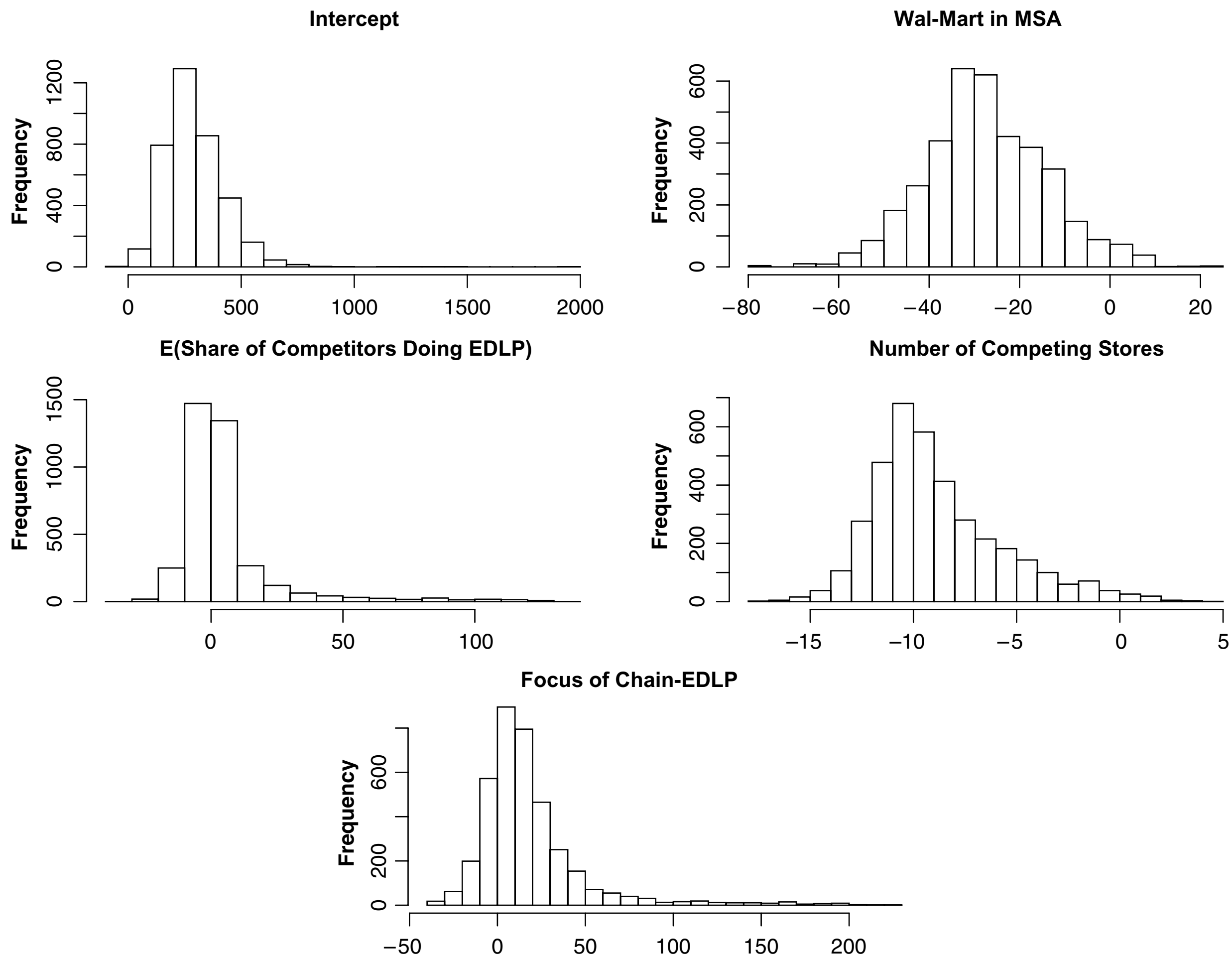
We now discuss the heterogeneity in revenues across markets and how various factors affect this heterogeneity. Our strategy for summarizing these results is to present histograms of effects across markets, which should be read alongside tables containing the 5th, 50th, and 95th percentiles of each across markets. We organize our discussion around four key variables of interest: (1) the revenue implications of Wal-Mart's presence, (2) the effect of local competition, (3) the effect of the similarity of the chosen pricing strategy with that chosen by local competitors, and (4) economies of scale and scope. Recall from our discussion in the "Econometric Assumptions and Empirical Strategy" section that we capture these effects by including the following variables: (1) a dummy for whether Wal-Mart operates in the firm's MSA (WM_{MSA}), (2) the number of rival firms in the market (N_{-i}), (3) the share of rival stores choosing the EDLP format ($\bar{a}_{-i}^{EDLP}$), and (4) the focus of the chain measured as a percentage of the chains' stores adopting strategy a [$FO_i(a = EDLP)$ and analogously $FO_i(a = PROMO)$]. Each of these variables is interacted with a full range of market demographics and included as right-hand-side variables in the revenue regression (see Appendixes A and B). 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 in market m, computed as follows:

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

where the $\hat{\theta}_R$ are the estimated coefficients of the interactions of the WM variable with market demographics in the revenue regression for the EDLP format reported in Appendix A. The $\hat{\theta}_R$ 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 FO_i (EDLP). Again, to provide a sense of the heterogeneity, we report the 5th, 50th, and 95th percentiles of these distributions in Table 8.

Observing the Wal-Mart effect in Figure 3, we note that 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 approximately \$28,000 per week (\$1.47 million annually). Note that this is a Wal-Mart effect specifically, not a competition effect more generally, because we have already controlled for the effect of the number of stores. 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 \$48,000 per week (\$2.5 million per year). These are typically larger, more isolated markets, in which Wal-Mart entry 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 \$9,580 per week (about \$500,000 per year). Observing 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 difficult to sign this effect. On the one hand, more EDLP stores in the local area implies stronger substitution and thus 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 difficult to drive deeper into these two stories. The main takeaway is that the data

Figure 3
REVENUE COMPONENTS OF EDLP



reveal that the cross-store substitution effect does not dominate in several markets.

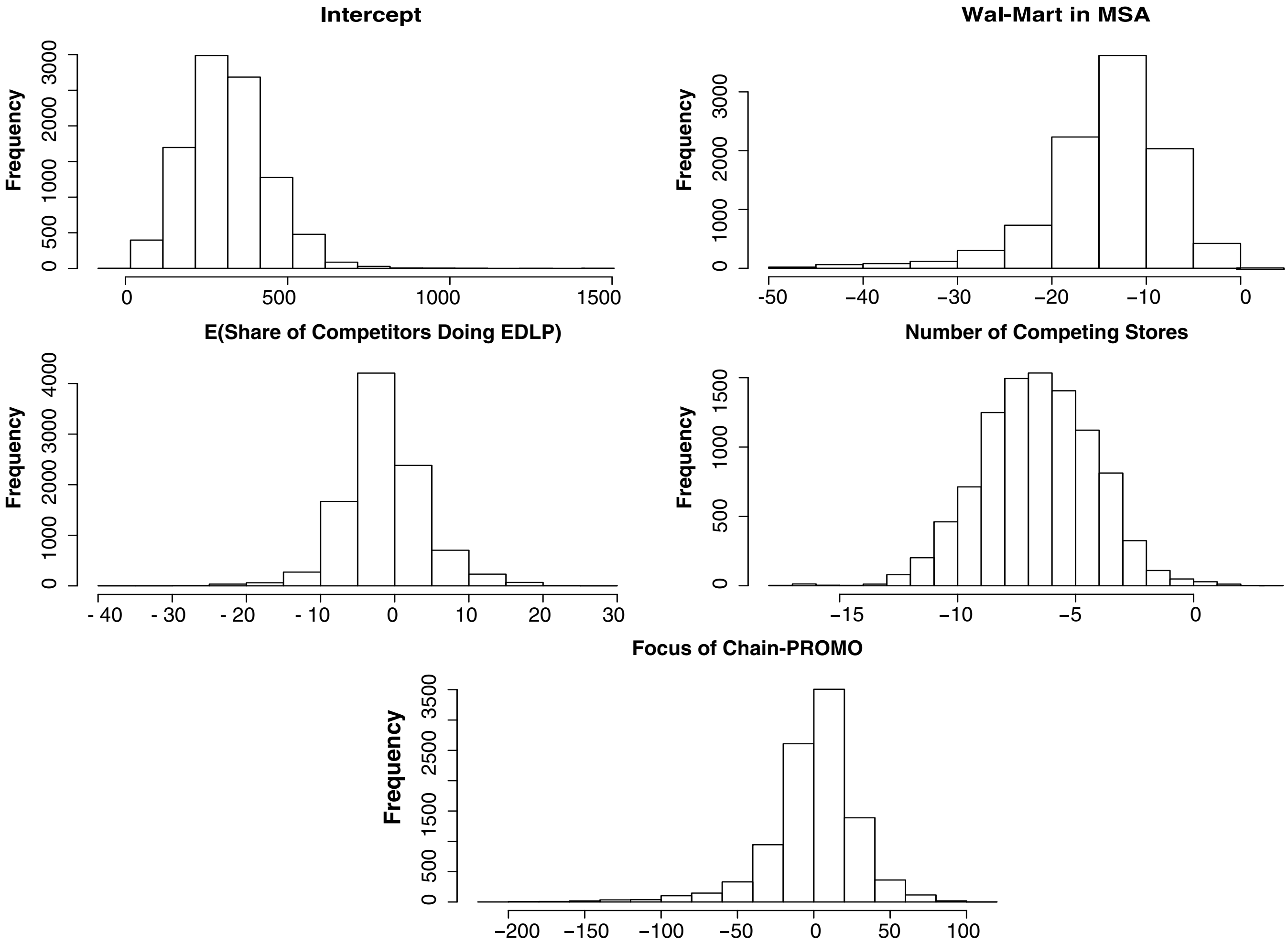
Figure 3 also reveals some evidence for economies of scope and scale on the demand side. In particular, supermarkets that have a larger proportion of stores outside the local market doing EDLP also tend to earn more under EDLP. This effect is fairly large. At the median, the economies add approximately \$11,100 per week (\$577,000 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 (i.e., 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 worthwhile to compare the numbers for the effects on PROMO revenues with the effects on revenues under EDLP. The effect on revenues of having a Wal-Mart in the MSA under PROMO is also negative, as expected, but it is significantly lower than under EDLP. At the median, the effect is a \$20,500 reduction in PROMO revenues per week (\$1.07 million annually). Comparing this with the effect of Wal-Mart presence for EDLP stores, we observe that Wal-Mart has a 38% larger effect on EDLP supermarket revenues than PROMO (\$1.47 million compared with \$1.07 million). It is evident that the EDLP positioning of Wal-Mart leads to stronger substitution with other EDLP stores in the local area than with other PROMO stores. Also notable is the evidence for scale and scope economies under PROMO, which contributes approximately \$39,200 per week (\$2.03 million annually) in a median store market. These tend to be higher than those of EDLP. This is not surprising, as communicating a coherent and consistent EDLP policy might be more difficult than claiming to have intermittent promotions and sales. We also observe that while competition has a negative impact on both formats, the prevalence of EDLP competitors tends to hurt PROMO stores more on average.

Costs

Next, we 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

Figure 4
REVENUE COMPONENTS OF PROMO



of individual effects across markets. Complete estimation results appear in Appendixes A and B.

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 that 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. Thus, 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 four years. Thus, the one-time switching costs should be thought of as borne over the four-year window.

In Figure 5 and Table 9, we observe that the median fixed cost is $293,750 per week under EDLP ($15.3 million annually) and $550,200 per week ($28.6 million annually) for PROMO stores. Note that this should not be compared directly with the median revenues reported in Table 8,

Figure 5
ESTIMATED FIXED COSTS

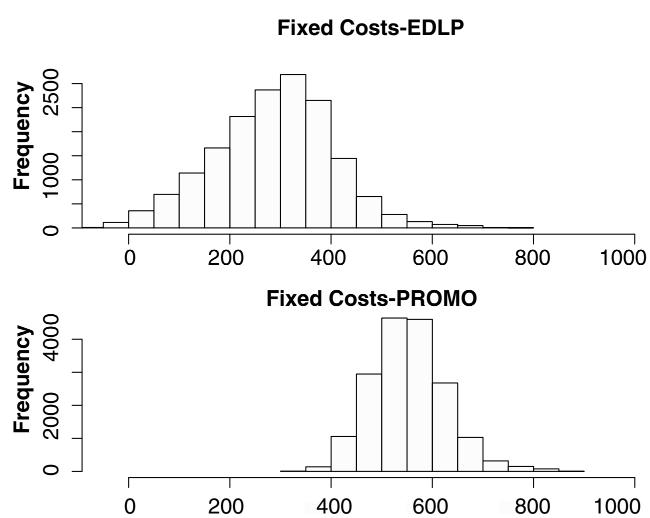


Table 9
DISTRIBUTION OF ESTIMATED COSTS

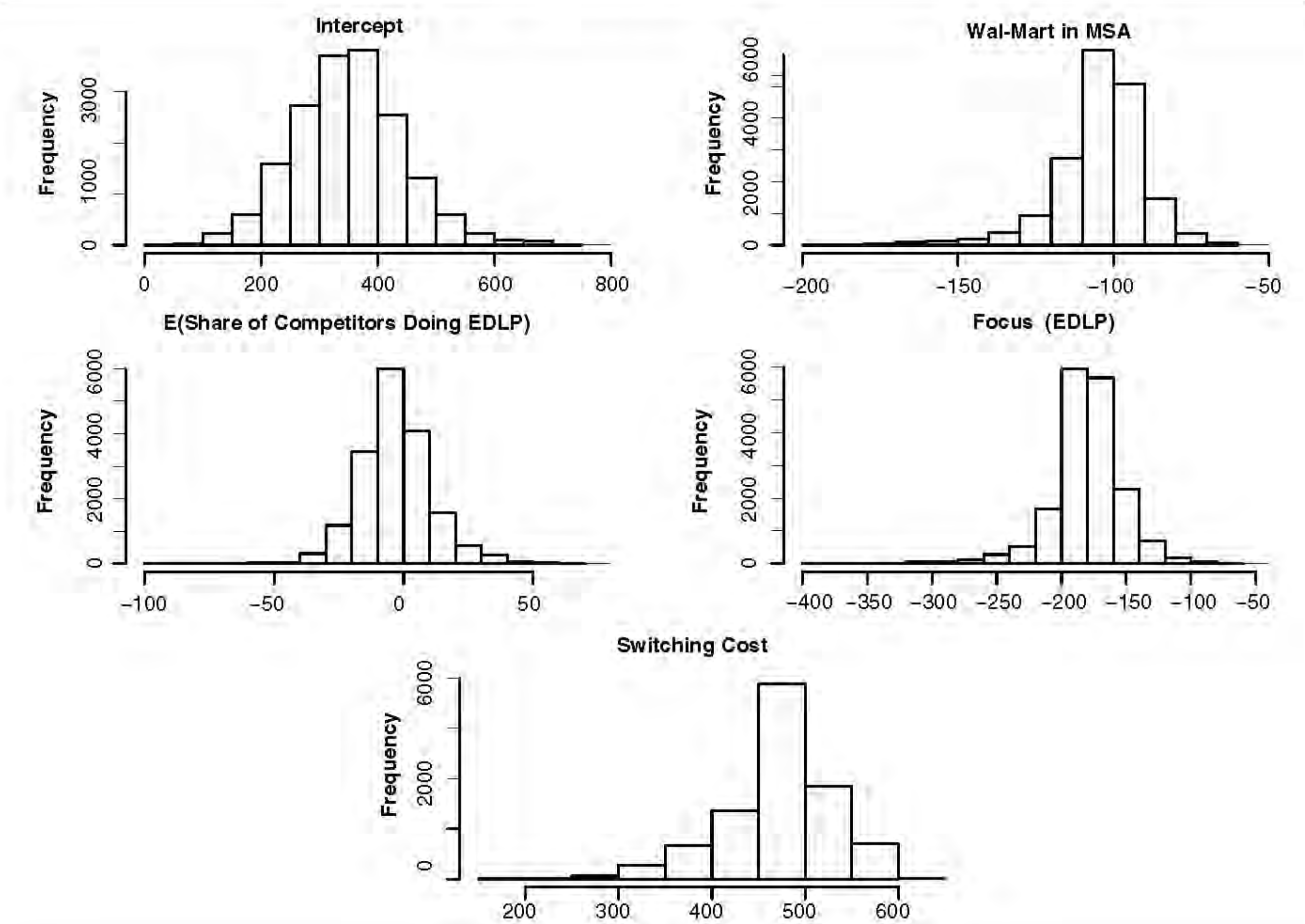
	5%	*50%*	*95%*
EDLP			
Intercept	201.20	349.04	510.47
Wal-Mart	−128.93	−102.75	−84.44
E(Share of competitors EDLP)	−24.33	−3.65	21.05
Focus of chain (EDLP)	−226.71	−179.66	−138.66
Total fixed costs (for Nonswitchers)	81.12	293.75	465.87
PROMO			
Intercept	433.89	538.61	665.55
Wal-Mart	17.17	27.05	35.60
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 Nonswitchers)	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

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 cost estimates. We estimate the median cost of switching from EDLP to PROMO as $11,100 per week, which works out to be approximately $2.3 million over a four-year horizon. We estimate the median cost of switching from PROMO to EDLP to be much larger, $477,300 per week, which works out to be approximately $99.3 million over a four-year horizon. This implies that the cost to the median EDLP store of switching to PROMO is approximately 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 that the switch from PROMO to EDLP is approximately 6 times more costly for the average firm in the distribution.

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

Figure 6
COST COMPONENTS OF EDLP



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, and the "EDLP focus" of the supermarket on fixed costs. We also report the distribution of estimated costs of switching to EDLP across markets. Figure 7 reports the same constructs for the costs of doing PROMO.

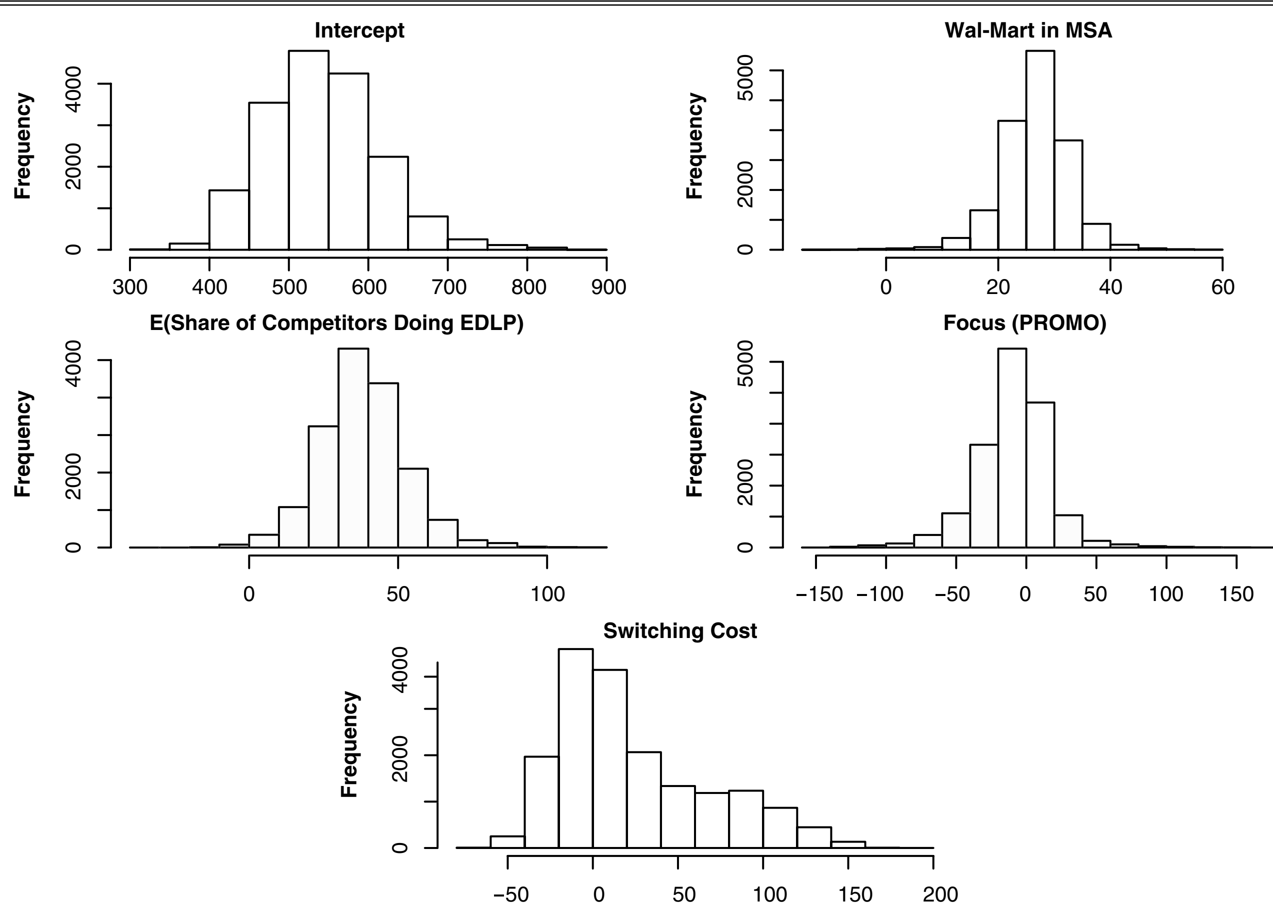
Examining Figure 6, we find that the presence of Wal-Mart in the supermarket's MSA reduces fixed costs of operation for the EDLP format. One interpretation of this result is that the presence of Wal-Mart lowers the costs of marketing an EDLP price positioning in a local market. For example, the presence 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 phenomenon. For example, when Wegmans (a regional supermarket chain in the northeast) moved from PROMO to EDLP in anticipation of Wal-Mart's entry, the supermarket made large investments in advertising and public relations to justify this repositioning to consumers, while also investing in reeducating and retraining their workforce (at stores and warehouses) to be attuned with the new strategy (several more examples that have been documented in the industry trade press are available on request in an unpublished appendix). 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 observe that 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 United States, the lower are its operating costs of running an EDLP supermarket in a local market. This is intuitive and in line with expectations.

Table 9 shows that 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 is approximately \$179,660 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 takeaway from these results is that scope economies in retailing operate over both revenues and costs.

Considering the results on the PROMO side in Figure 7, we observe that 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

Figure 7
COST COMPONENTS OF PROMO



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 incremental revenue of approximately $6.2 million compared with EDLP. Whereas EDLP does offer lower fixed costs of operation, the cost of switching from PROMO to EDLP is estimated to be approximately six times larger than that of switching from EDLP to PROMO. Furthermore, 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.

Robustness and Simulations

Common unobservables. Next, we discuss the robustness of our estimates to the presence of common, market-level unobservables. A potential concern involves selection issues arising from unobservables common across firms in a market, which might drive firms' actions. This is a recurring but difficult 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 counterintuitive finding that firms prefer to enter markets with more competition. To assess whether this is an issue, we reestimate our revenue regressions with market-level (MSA) random effects. Although 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 greater than .9. However, including unobservables into revenues greatly complicates the structure of the dynamic choice problem if these unobservables are included in the players' information sets. Treating these unobservables 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.

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 United States. Our goal is to informally verify that at the estimated parameters, the model predicts, consistent with actual evidence, that there will not be significant en masse switching by supermarkets into EDLP, as some had predicted in the early 1990s. We simulate a simple counterfactual by assuming that the industry state includes the presence of Wal-Mart in all markets. We then forward-simulate 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 beginning from the 1998 conditions does push more market participants toward EDLP, but not overwhelmingly. In particular, the overall effect is on the order of an 18.8% increase in EDLP adoption across the entire United States (34.01% of active supermarkets chose to be EDLP in the counterfactual steady state, compared with 28.7% in the data). At the same time, market structure is also pushed toward higher concentration, because exits in the steady state are approximately 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 that the U.S. market would tip toward EDLP.

CONCLUSIONS

This article makes 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 such as firm's repositioning costs. Second, we cast empirical light on an age-old question in the marketing of consumer packaged goods: the costs and benefits of using EDLP versus PROMO. Despite the significant interest in this topic, a full accounting of the long-term costs 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 increases understanding of the economics of the supermarket industry and the determinants of long-term market structure. Third, we illustrate how observed switches combined with auxiliary postgame data (e.g., revenues, prices, 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 further 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 shed light on 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. Although 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 the scope of our current analysis. Finally, extending our framework to allow for rich layers of persistent unobserved heterogeneity would be an important direction forward. This is an active area of frontier econometric research. We intend to address some of these extensions in further study. We hope our current work spurs further interest in the dynamics of pricing and repositioning in the field.

Appendix A
REVENUE REGRESSION ESTIMATES

		PROMO		EDLP	
Variable	*Interactions*	*Estimate*	*SE*	*Estimate*	*SE*
Intercept	Constant	−143.4917	38.4107	2.7606	37.6958
	pop	.0018	.0003	.0016	.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	.0019	.0004	.0023	.0004
	size	7.1859	.1294	7.5947	.1838
	Tstores	.0099	.0012	−.0021	.0017
Wal-Mart	Constant	3.4924	18.9370	40.0459	26.8277
	pop	−.0001	.0001	.0000	.0002
	hhsize	.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	−.0001	.0002	−.0007	.0004
E(Comp EDLP)	Constant	45.4532	23.3660	−11.8019	35.9686
	pop	.0000	.0002	−.0005	.0003
	hhsize	−16.0171	8.4788	6.4146	13.4419
	p_black	18.2148	12.6664	4.5995	19.9579
	p_urban	−15.2756	1.2790	7.1724	11.4828
	p_hisp	21.1111	20.4637	129.1107	32.3871
	h_inc	.0002	.0002	−.0001	.0005
Focus PROMO/EDLP	Constant	185.2156	42.4260	−120.8199	45.5139
	pop	−.0006	.0003	−.0007	.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	.0006	.0004	−.0007	.0006
Number of Competing Stores	Constant	3.4682	4.4740	1.9628	6.2802
	pop	−.0001	.0000	.0000	.0000
	hhsize	−.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	−.0001	.0000	.0000	.0001

Appendix B
COST REGRESSION ESTIMATES

		PROMO		EDLP	
Variable	*Interactions*	*Estimate*	*SE*	*Estimate*	*SE*
Intercept	Constant	−40.8906	31.1996	486.5116	29.4313
	pop	.0004	.0003	.0011	.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	.0023	.0003	.0027	.0003
	size	4.0016	.0642	3.2505	.0654
	Tstores	−.0475	.0014	−.0329	.0012
	VI	5.5494	1.8091	15.8291	1.7537
Wal-Mart	Constant	36.1164	31.2078	71.0421	24.9721
	pop	−.0005	.0002	.0003	.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	.0002	.0003	.0002	.0003
E(Comp EDLP)	Constant	119.4247	21.2418	100.7033	18.6769
	pop	.0006	.0002	.0008	.0002
	hhsize	−37.3200	8.2631	−22.6546	6.9649
	p_black	−.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	.0001	.0003	−.0003	.0002
Focus PROMO/EDLP	Constant	131.8787	36.4711	−223.9241	32.9406
	pop	−.0002	.0003	−.0001	.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	.8312	36.8522	−145.0459	40.7833
	h_inc	.0010	.0004	−.0015	.0004
Switching Costs	Constant	768.8435	27.2031	146.8000	25.4979
	pop	.0003	.0002	−.0008	.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	−.0001	.0003	.0006	.0002
	WalMart in MSA	−107.2976	4.9895	29.7865	4.7857
	E(Comp EDLP)	−17.5035	4.1388	−.6812	4.5161
	Focus	−114.9448	7.0153	−123.5959	6.8326

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