Measuring the Cost of Supermarket Promotions

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Measuring the Promotional Costs of Supermarket Retailers

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Abstract

Pressured by competition and by consumers who have come to expect frequent price discounts, retailers have fallen into a price-promotion trap. The widespread use of retail promotions and the magnitude of dollars spent on them call economists to explore the complex of merchandising decisions. In this study, I estimate the marginal cost of price promotion in the retail industry, in order to examine the role of promotional costs in shaping the coordination of pricing and promotion. The estimates imply that the marginal cost of promotion ranges from \$0.97 to \$4.98 per promotion, and the total promotion cost comprises 3.6 to 17.1 percent of store revenues, or 10.4 to 23.7 percent of profits. The results also indicate that stores with higher promotion elasticities are able to afford more expensive promotions. Stores with higher promotion costs, however, have to offer deeper price discounts in order to attract more store visits.

Keywords: Promotion costs; moment inequality; retail.

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1 Introduction

As weekly grocery shoppers, we observe the volatility in retail prices and promotions offered by supermarkets. Supermarket retailers adjust retail prices on a weekly basis, and change the set of promoted products time to time. Pressured by competition and by consumers who have come to expect frequent price discounts, retailers have fallen into a price-promotion trap. Although only 20% percent of retail sales come from promotions, supermarkets devote about 80% of their week managing them (Bolton et al., 2010). Promotions - advertised price information - allow consumers acknowledge particular products, inform them about temporary price cuts, or both. The price information nowadays is sent to potential consumers via a variety of media forms, including flyers, on-line circulars, e-mails, and mobile apps that recently emerged.

Despite the widespread use of retail promotions and the magnitude of dollars spent on them(Levy et al., 1997), much remains unknown about the determination of the complex pricing strategy. Supermarkets use different price positionings, including everyday low price (EDLP, offers consistently low prices), high-low pricing (HiLo, offers temporary price discounts), and high-tier pricing(HT, offers high prices with few temporary price cuts). The major difference among the positionings lies in the average price. For example, EDLP stores are usually characterised by low average prices, as it claims, either because they have bigger bargaining power with manufactures, or because they give up the promotion funds from manufactures used to support merchandising activities. However, regardless of price positioning, we observed promotions exist in all kinds of stores – from Wal-Mart to Whole Foods. On the other hand, the coordination of pricing and promotion decisions varies largely across stores. EDLP stores offers smaller sets of promoted products than regional HiLo chains; In additional to promotion, HiLo chains also offer deep price discounts; TH stores do have some promotions, but the prices of promoted items are still of regular prices in most cases.

Supermarket managers clearly understand the shopping behavior of consumers well: since there are economies of scale in shopping, once at a store, consumers will buy other items in addition to the promoted products. Therefore, retailers compete on the basis of the total basket surplus, and the promoted products with deep price discounts serve as a tool of attracting store visits as well as business stealing. In this sense, the promotional costs can be offset as long as the additional profits generated by increased store visits of basket shoppers is greater than its negative contribution(Bliss, 1988; Lal and Matutes, 1994). Since a given discount on any one good in the bundle will have a similar effect on consumers' likelihood of visiting that retailer, it calls retails to optimally choose the product that could generate the highest profits (Gauri et al., 2008). That is, managers should choose the brands and product categories that are most effective in luring consumers coming into the store. Said differently, retailers should minimize the loss at a given basket surplus offered(Hosken and Reiffen, 2007). As a result, the problem of a supermarket retailer becomes the optimal pricing and promotion decisions that maximizes store-level profits, facing multi-category demand.

The *total* costs of promotions largely depend on the trade promotion budgets negotiated between retailers and manufactures, while the *marginal* promotion cost depends on operating efficiency, size of chain, factors that affect labour costs, and so on. Perhaps we could get an idea how significant the total expenditure spent on merchandising activities is by looking at retailers' financial statements, but they are limited in helping us understand how the sophisticated pricing decisions are made for every single product carried by retailers.

The goal of this paper is to examine the role of promotion cost in shaping the strategic coordination of pricing and promotion across retailers with heterogeneous promotion costs. In fact, promotion and price discounts do not always come together – some products are promoted even at quite high prices (so consumers are attracted not because of the price, but acknowledging the product itself). By introducing promotional cost, I am able to model retails' pricing decisions facing the tradeoff between paying additional promotion costs and obtaining more store visits, and therefore profits, generated by price promotions. In each period, retailers choose the price of each product and decide whether to promote it to maximize store-level profits. A promotional cost will incur accordingly for each promoted product. Promotion and pricing decisions are coordinated, in the sense that only non-regular priced products can be promoted.[1] Due to the nature of multi-category shopping behavior, a small set of promoted products could make the store attractive enough for some consumers.

Using scanner data of basket-shopping households and the associated store merchandising information, I estimate the promotional cost with moment inequality estimation. This methodology allows me to circumvent the dimensionality issues(the size of action set increases exponentially with the number of products typically carried by supermarkets). The estimation procedure is based on the necessary condition of profit maximization - the agent chooses strategies according to her expectations lead to profits at least as high as feasible alternatives. By estimating demand ahead, I am able to predict sales and therefore profits, would have changed if the retailer had made alternative decisions. The difference between actual and counterfactual profits provides the bounds in promotion costs.

The estimates imply that the marginal cost of promotion ranges from \$0.97 to \$4.98 per promotion, and the total promotion cost comprises 3.6 to 17.1 percent of store revenues, or

[1] Though most promotions are accompanied by price reductions, I allow for promotion even if priced higher than regular level, as empirically observed.

10.4 to 23.7 percent of profits. The results also indicate that stores with higher promotion elasticities are able to afford more expensive promotions. Therefore, those stores have to offer deeper price discounts, expecting more store visits, in order to cover the promotion costs and the negative contribution of price cuts. As a result, the high promotion cost retailers tend to simultaneously offer promotion and (deep) price discounts.

This study would improve previous works in two dimensions. First, pricing and promotion are often studied almost in isolation of each other. Pricing and promotion decisions made by different managers in different departments increase the possibility of *sub-optimal* decisions on both fronts. However, many studies show that retailers can improve the effectiveness of promotion by coordinating them with pricing decisions(Bolton and Shankar, 2003; Bolton et al., 2010). Second, the multi-category pricing model is able to provide unbiased estimation in price and promotion elasticities. Single-category models will generate biased upward-sloping demand curves estimated using store or chain level data, because of the difficulty in distinguishing between movements of a store's demand curve (from having more customers in the store) versus movements along a demand curve (resulting from changes in price). The predicted profits at alternative pricing and promotion decisions will be biased if use the biased demand estimates.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the dataset and presents preliminary analysis. Section 4 presents the problem of retailer and the model of demand. Section 5 explains the estimation procedure, including how I construct counterfactuals. Section 6 contains the main results and section 6 concludes.

2 Data

I use the same database as (Bell et al., 1998), where they investigate how various costs of shopping affecting store choice. The database originally provided by IRI comes from a large metropolitan area in the US and contains 104 weeks of data (June 1991 to June 1993). The dataset has two components, the household level data and the store data. The individual household data contains information on the grocery shopping behavior of 548 households at five different supermarkets: purchase histories of multiple categories and brands, demographics (family size, household income, etc), and zip -code-approximated home-store distances of each household. The store level data contains information on merchandising information (weekly pricing and promotion information) for each UPC of 24 available categories at five stores, labelled as EDLP (everyday low price), HiLo (high-low pricing), and HT(high-tier) stores with different pricing positionings.

In this section, I present the multi-category profit maximization problem of oligopoly retailers, facing the demand of basket shoppers. The market has S retailers and H households. A retailer $s \in \{1, ..., S\}$ carries multiple categories of products, $c \in \{C\}$, and different brands of products within each category, $j_c \in \{J_c\}$. In each period t, a household $h \in \{1, ..., H\}$ purchases goods for her consumption needs, given her information on prices and promotional activities of the retailers. A household first chooses the store she will visit based on these information, then, once at the store, chooses at most one product for each category. In every period, the retailers make pricing and promotional decisions for all products. If a product is chosen to be a featured product, a promotional cost will incur.

I make the following assumptions. To rationalize multi-category pricing, the object of each store is to maximize store-level profit. Promotional activities are store decisions, opposing to manufactures' decisions. Stores bare the costs of price advertising. In each period, a household chooses at most one store for shopping (one-stop shopping). The model does not allow households to choose multiple stores to assembly her basket. Households are passively exposed to price advertise sent out by stores, through whatever media forms. The probability that a household read the ads is independent across stores and is common for all households. These probabilities are specified by a vector $\phi = (\phi_1, ..., \phi_S)'$.

2.1 Shopping Behaviors

In each period, a household makes two kinds of decisions: the choice of brand for each category, and the choice of store. The household is assumed to choose at most one brand within each category and at most one store. Following (Bell and Lattin, 1998), the household will visit the store that offers the greatest expected total utility, U_{sht}, which consists of store merchandising attractiveness u_{sht}, the disutility of commuting between home and store $c(\cdot)$, and store valuation λ_s:

$$\begin{aligned} &s^*_{ht} \in \arg\max_s U_{sht}, \\ &U_{sht} = c(dist_{sh}, \theta_d) + \lambda_s + \theta_u u_{sht} + \zeta_{sht} \end{aligned} \tag{1}$$

where ζ_{sht} is the idiosyncratic shock that accounts for randomness of store preferences, assumed i.i.d. type I extreme value distributed. She will visit store s with probability

$$\eta_{sht} = \frac{\exp(c(dist_{sh}, \theta_d) + \lambda_s + U_{sht})}{1 + \sum_{q \in S} \exp(c(dist_{qh}, \theta_d) + \lambda_q + \theta_u U_{qht})} \tag{2}$$

The deterministic utility of the outside option, no shopping, is normalized to zero, thus $U_{0ht} = \zeta_{0ht}$. The total merchandising attractiveness u_{sht} equals the category attractiveness summing over all categories:

$$u_{sht} = \sum_c v_{shct} \tag{3}$$

The brand choices and the expected store attractiveness depend on ads exposure. If a household reads price information sent out from store s, then she has no uncertainties on prices of featured products that appear on circulars. Furthermore, she is assumed to be able to infer that the unadvertised products are priced at regular levels. On the other hand, a consumer not exposed to ads by s forms expectation on brand choices according to her belief on store behaviors, $F_s(P, M)$, the joint distribution of prices and marketing activities(P denotes prices and $M = (M^F, M^D)'$ that denotes "feature" and "display"). Let a dummy vector ad denote the status of ad exposure: $prob(ad_s = 1) = \phi_s$ and $prob(ad_s = 0) = 1 - \phi_s$.

If household h is informed about prices of store s, $ad_s = 1$, for each category $c \in C$, she chooses a brand $j_c \in \{J_c\}$ that maximizes the category utility:

$$j_c \in \arg\max_{j \in J_c} w_{sht,j_c} \tag{4}$$

where w_{sht,j_c} is the indirect utility she obtains from purchasing product j_c, given by

$$\begin{aligned} w_{sht,j_c} &= \chi_c + \xi_{j_c} + \beta M_{st,j_c} + \alpha p_{st,j_c} + \epsilon_{hst,j_c} \\ w_{sht,0_c} &= \epsilon_{hst,0_c} \end{aligned} \tag{5}$$

where χ_c is the intrinsic utility of category c invariant over brands, ξ_{cj} is the average brand evaluation, M_{st,j_c} denotes the marketing activities that include two components, "display", M^D_{st,j_c}, and "featured", M^F_{st,j_c}. p_{st,j_c} is the price, and ϵ_{hst,j_c} is an idiosyncratic shock which is assumed to follow type I extreme value distribution, i.i.d. across stores, categories, brands, households, and periods. Finally, the deterministic utility of the outside option, not purchase category c, is normalized to zero. Since the flyers do not provide information on "display", I assume an consumer infers $M^D_s = 0$ prior to shopping. Let $\tilde{s}$ and $\tilde{v}$ be the posterior choice probabilities and category utility conditional on store choice and category choice (as if the household had already arrived at s and all information is realized). They are given by

$$\begin{aligned} \tilde{s}_{sht,j_c} &= \frac{\exp(\xi_{j_c} + \beta M_{st,j_c} + \alpha p_{st,j_c})}{1 + \sum_{k_c} \exp(\xi_{k_c} + \beta M_{st,k_c} + \alpha p_{st,k_c})}, \\ \tilde{v}_{sht,j_c} &= \ln \sum_{j_c} \exp(\chi_c + \xi_{j_c} + \beta M_{st,j_c} + \alpha p_{st,j_c}) \end{aligned} \tag{6}$$

Thus, the prior brand choice probabilities and the expected category attractiveness are their posterior counterparts at $M^D_{st,j_c} = 0$:

$$\begin{aligned} s_{sht,j_c}(ad_s = 1) &= \tilde{s}_{sht,j_c}(M^D_{st,j_c} = 0), \\ v_{shct}(ad_s = 1) &= \tilde{v}_{sht,j_c}(M^D_{st,j_c} = 0), \end{aligned} \tag{7}$$

If $ad_s = 0$, then the brand choice probabilities and the expected category attractiveness are integrals that integrate over the joint distribution of prices and marketing activities, $F_s(P, M)$:

$$\begin{aligned} s_{sht,j_c}(ad_s = 0) &= \int s_{sht,j_c}(ad_s = 1) dF_s(P, M), \\ v_{shct}(ad_s = 0) &= \int s_{sht,j_c}(ad_s = 1) dF_s(P, M). \end{aligned} \tag{8}$$

Her final store choice probabilities depend on the merchandising activities of all stores as well as her ads exposure, ad, given by

$$\eta_{sht}(ad) = \frac{\exp(c(dist_{sh}, \theta_d) + \lambda_s + \theta_u u_{sht}(ad_s))}{1 + \sum_{q \in S} \exp(c(dist_{qh}, \theta_d) + \lambda_q + \theta_u u_{qht}(ad_q))}. \tag{9}$$

Note that "display" does not affect the prior store and brand choices, and that M^F affects the expected store choices only through the exposed consumers.

2.2 Pricing Strategy

The retailers simultaneously make pricing and merchandizing decisions in each period to maximize the expected total store profit [23] . Since stores usually do not track marketing activities in rival stores or sneak into rival stores to peep current marketing activities, as documented in the marketing literature. The information set of store s does not include current or past activities. However, each store has a belief on rivals' activities, specified by the joint distribution of prices and merchandising, $F_{p,m,s}$. As a result, store s would treat consumers who does receive price information from rival stores as uninformed consumers (by its rivals), because s does not know the current decisions at rival stores. Therefore, store s believes that the probability of visiting s depends on its own advertising coverage and prices, not on rivals' advertising coverage or prices.

[2]Some studies in the marketing literature assume category managers maximizes respective category profit, opposing to a store manager maximizes store profit, see (Bolton and Shankar, 2003; Bolton et al., 2010).

[3]Pricing and promotion decisions are made by different managers in different department in some retail chains(Ailawadi et al., 2009). Ads decisions conditional on prices increase the possibility of sub-optimal decisions.

For each product j_c, store s has to make pricing and promotion decisions, p_{st,j_c} and m_{st,j_c}. A promotional cost θ_m will incur if the product is chosen to be feature advertised. The pricing decision set of each product, assumed exogenous and discrete, consists of all empirically observed prices in that store. The objective of store s is to choose the optimal price and promotion variables to maximize the expected profits:

$$(p_{st}, m_{st}) \in \arg\max_{p,m} E\left[\pi_{st}|J_{st}\right], \tag{10}$$

where J_{st} is the agent's information set at the time of the decisions that contains $F_{p,m,s}$ and knowledge on demand. Note that there can be prediction error due to randomness in observed profits that is not known at the time decisions are made. For example, a store s's expectation on m^f_{-st} would differ from the outcome. Let $R_{st}(\cdot)$ denote the period t profit across all categories excluding promotional costs. The expectation error is denoted by $e_{st} = R_{st}(\cdot) - E[R_{st}(\cdot)|J_{st}]$, and is mean zero conditional on the information set by construction, i.e., $E[e_{st}|J_{st}] = 0$.

As stated above, the ads exposure affects the expected store attractiveness which in turn affects store choice. The expected profits are therefore function of ad coverages, ϕ_s. Let mc_{st,j_c} denote the marginal cost of j_c, and let θ_m be the marginal cost of promotion. The expected per period profit is $R(\cdot)$ minus the total promotional cost, which is assumed proportional to the number of products on price advertising, $\theta_m \cdot (\mathbf{1}' m_{st})$. The profit is given by

$$\begin{aligned}
&\pi_{st}(p_{st}, m_{st}|J_{st}) \\
=&R_{st}(p_{st}, m_{st}|J_{st}) - \theta_m \cdot (\mathbf{1}' m_{st}) \\
=&\sum_h \phi_s \cdot \left(\eta_{hst}(ad_s = 1, ad_{-s} = 0) \sum_c \sum_{j_c \in J_c} s_{sht,j_c}(ad_s = 1, ad_{-s} = 0) \cdot (p_{st,j_c} - mc_{st,j_c})\right) \\
+&\sum_h (1 - \phi_s) \cdot \left(\eta_{hst}(ad_s = 0, ad_{-s} = 0) \sum_c \sum_{j_c \in J_c} s_{sht,j_c}(ad_s = 1, ad_{-s} = 0) \cdot (p_{st,j_c} - mc_{st,j_c})\right) \\
-&\theta_m \cdot (\mathbf{1}' m_{st}).
\end{aligned} \tag{11}$$

3 Estimation

My Estimation of the behavioral model will implement two major methodologies. First, the demand system will be estimated using simple logit regression and simulation methods.[4] Second, the promotional cost parameter will be estimated using moment inequality method.

3.1 Demand

I estimate the demand preferences assuming static demand and time-invariant belief in prices. In stage one, I estimate parameters related to brand choices ($\Theta_{h1} = (\xi, \beta, \alpha)'$) conditional on purchases. To account for the possible correlations between merchandising decisions and unobservables, I use brand dummies and average price at each store as instruments. The endogeneity issues considered here include (1)higher-quality items tend to be priced higher, (2)unobserved wholesale price variations that are correlated with retail price, and (3)popular items on promotion more frequently than less popular ones. Brand dummies can be used as IV to control for (1) and (3). To account for 2, unobserved store-specific factors, such as wholesale price and operation costs, I use average price at each store as an IV.[5]

In stage two, parameters related to store choices are estimated by maximizing the probability of the observed store choices given $\hat{\Theta}_{h1}$. Since ads exposure affects store attractiveness, the likelihood of store choice depends on exposure status, *ad*. There are 2^S possible exposure statuses in total (permutations of exposure dummies). Denote the set of all permutations by AD. Because the expected choice probabilities and purchase utilities in (**??**)) have no closed forms, they must be calculated by simulation drawing prices from the empirical distribution, $F(P, M)$. The likelihood function of store choice is give by

$$\begin{aligned} l_{store}(\phi, \Theta_{h1}, \Theta_{h2}) &= \sum_t \sum_h \sum_{ad \in AD} prob(ad) \cdot \log\ store_{ht}; \Theta_{h1}, \Theta_{h2}) \cdot \mathrm{I}(store_{ht} = 1) \\ &= \sum_t \sum_h \sum_{ad \in AD} prob(ad) \cdot \log\ \eta_{sht}(ad; \Theta_{h1}, \Theta_{h2}) \cdot \mathrm{I}(store_{ht} = 1) \end{aligned} \tag{12}$$

where $\Theta_{h2} = (\theta_d, \theta_u, \lambda)'$. The estimates of ϕ and Θ_{h2} are the parameters that jointly maximize the likelihood:

$$(\phi, \Theta_{h2}) \in \ \arg\ \max l_{store}(\phi, \hat{\Theta}_{h1}, \Theta_{h2}) \tag{13}$$

[4] Although (Bell et al., 1998) and I use the same data set to estimate consumer preference on store choice and brand preferences, there are two major differences in estimation. First, Different sets of products are chosen to form aggregate store attractiveness. I use a wider range of categories. Also I include all products within each category, instead of using only the "big players", therefore my choice set of each category is bigger. Second, (Bell et al., 1998) assume full information on prices and promotions for consumers' store choice problem.

[5] (Nevo, 2001) proposes and uses them as IV

3.2 Pricing Decisions

The traditional approach to the structural estimation of models of binary choices relies on deriving choice probabilities from the theoretical framework, and choosing the parameter values that maximize the likelihood of the choices observed in the data. This approach is not feasible in this setting because writing the choice probabilities involves examining the dynamic implications of every possible combination of promotions and prices.

Given the cardinality of the choice set (supermarkets typically carry $\#J > 20{,}000$ products), computing the value function corresponding to each of its elements is impossible with currently available computational capabilities. I avoid this complication by using moment inequalities as the estimation method that preserves the discrete nature of the variable. Moment inequality estimators require neither computing the value function of the retailers nor artificially reducing the dimensionality of the choice set.

Identification of the parameters is based on the condition that a store's expected profits from its observed choice are greater than its expected profits from alternative choices. The inequalities come from applying an analogue of Euler's perturbation method to the dynamic discrete choice problem. Let $M_T = \{M_t, M_{t+1}, M_{t+2}, ..., M_T\}$ denote the sequence of *binary* decisions. I consider small deviations from the actual decisions on product j_c in time t, $M_T^{'} = \{M_t^{'}, M_{t+1}, M_{t+2}, ...\}$. Since in the counterfactual the manager makes different decisions, the counterfactual profits contains different menu costs and/or promotional costs. A necessary condition for profit maximization is that for all stores, each store's expected profit from choosing actual P_T and M_T is at least as good as its expected profit from alternative choices:

$$E_t \left[V_s(M_T, P_T) | J_{st} \right] \geq E_t \left[V_s(M_T^{'}, P_T^{'}) | J_{st} \right], \tag{14}$$

where $V(\cdot)$ denotes the total expected profits. The difference between the actual and the counterfactual profits provides the boundaries of menu costs and promotional costs. I consider the following four situations to construct alternatives.

1. Drop a temporary promotion. Constructing the counterfactual requires a temporary price cut accompanied by promotion on product j_c, that is, $p_t < p^{reg}$, $p_{t-1} \geq p^{reg}$, $p_{t+1} \geq p^{reg}$, and $m_t^f = 1$ (to simplify the notation, I will omit the product and store subscripts). Keeping the price sequence and promotion sequence of all other products unchanged, an counterfactual V can be generated from an alternative promotion sequence of product j_c without the time t promotion, $m_t^{'} = 0$. Let $\tilde{\pi}$ denote the per period profit excluding the menu cost and promotional cost. Dropping off the time t promotion saves the promotional

cost. The actual and counterfactual profits are

$$\begin{aligned} V(M_T, P_T) &= \tilde{\pi}_t(P_t, M_t) - \theta_m + \delta V_{t+1} \\ V(M_T^{'}, P_T) &= \tilde{\pi}_t(P_t, M_t^{'}) + \delta V_{t+1}. \end{aligned} \tag{15}$$

Since the state of period $t+1$ will not be affected by $M_T^{'}$, a small deviation in M is simply a static perturbation. The moment inequality condition is

$$\theta_m \leq \tilde{\pi}_t(P_t, M_t) - \tilde{\pi}_t(P_t, M_t^{'}) \tag{16}$$

2. Add a temporary promotion. It requires the actual promotion decision is zero at a price cut: $p_t < p^{reg}$, $p_{t-1} \geq p^{reg}$, $p_{t+1} \geq p^{reg}$, and $m_t^f = 0$. The deviation is $m_t^{'} = 1$. Similarly to situation 1, I have

$$\theta_m \geq \tilde{\pi}_t(P_t, M_t^{'}) - \tilde{\pi}_t(P_t, M_t) \tag{17}$$

3. Drop a temporary price adjustment and the accompanied promotion. This applies to the commonly impressed events where a price cut comes with promotion, but I need the price cuts last for two periods, because simply dropping a one-period price cut will change the state variable in $t+1$. In period t, price is cut from a high price p_{t-1} to a low price p_t and accompany it with promotion, incurring menu cost and promotional cost, then keep it unchanged for one period but without promotion, and raise it back to a high level in $t+2$, incurring another menu cost. That is, $p_{t-1} \geq p^{reg}$, $p_t = p_{t+1} < p^{reg}$, $p_{t+2} \geq p^{reg}$, and the prices before and after the two-period cuts are unequal, $p_{t-1} \neq p_{t+2}$. The alternative decision sequence is to let price stay on its $t-1$ level, drop promotion in t, and change it to the $t+2$ level: $p_t^{'} = p_{t+1}^{'} = p_{t-1}$, $m_t^{'} = 0$. In the alternative, no menu cost promotional cost is paid in t. The actual and counterfactual values are

$$\begin{aligned} V(M_T, P_T) &= \tilde{\pi}_t(P_t, M_t) - \theta_m - \theta_p + \delta\tilde{\pi}_{t+1}(P_{t+1}, M_{t+1}) + \delta^2 V_{t+2} \\ V(M_T^{'}, P_T^{'}) &= \tilde{\pi}_t(P_t^{'}, M_t^{'}) + \delta\tilde{\pi}_{t+1}(P_{t+1}^{'}, M_{t+1}) + \delta^2 V_{t+2}. \end{aligned} \tag{18}$$

The moment inequality condition is

$$\theta_m + \theta_p \leq \tilde{\pi}_t(P_t, M_t) + \delta\tilde{\pi}_{t+1}(P_{t+1}, M_{t+1}) - \tilde{\pi}_t(P_t^{'}, M_t^{'}) - \delta\tilde{\pi}_{t+1}(P_{t+1}^{'}, M_{t+1}) \tag{19}$$

4. Add both price changes and promotion. I target the cases where prices stays high for consecutive several periods and no promotion occurs. I require the actual decision sequence is $p_{t-1} = p_t = p_{t+1} \neq p_{t+2}$, $p_{t-1} \geq p_{reg}$, $p_{t+2} \geq p_{reg}$, and $m_{t-1} = m_t = m_{t+1} = 0$. In the alternative I let price drop in t and the product promoted, incurring both menu cost and

promotional cost, and make no price change or promotion in $t+1$, then raise price to its $t+2$ level: $p_t^{'} = p_{t+1}^{'} < p_{reg}$, $m_t^{'} = 1$. I have

$$\begin{aligned} V(M_T, P_T) &= \tilde{\pi}_t(P_t, M_t) + \delta\tilde{\pi}_{t+1}(P_{t+1}, M_{t+1}) + \delta^2 V_{t+2} \\ V(M_T^{'}, P_T^{'}) &= \tilde{\pi}_t(P_t^{'}, M_t^{'}) - \theta_m - \theta_p + \delta\tilde{\pi}_{t+1}(P_{t+1}^{'}, M_{t+1}) + \delta^2 V_{t+2}. \end{aligned} \tag{20}$$

and the moment inequalities

$$\theta_m + \theta_p \geq \tilde{\pi}_t(P_t, M_t) + \delta\tilde{\pi}_{t+1}(P_{t+1}, M_{t+1}) - \tilde{\pi}_t(P_t^{'}, M_t^{'}) - \delta\tilde{\pi}_{t+1}(P_{t+1}^{'}, M_{t+1}) \tag{21}$$

Thus, by estimating demand in stage 1 and 2, I am able to predict counterfactual revenue and profits, in order to form the upper and lower bounds of $\hat{\theta}_m$. Let ΔR denote the different between actual revenue and counterfactual revenue. I can write N_s inequalities for each store s, where each inequality represents the deviation from what the supermarket actually did:

$$E\left[\Delta R_n | J\right] - \theta_m \geq 0, \;\; n = 1, ..., N_s \tag{22}$$

At the true parameter, the identified set of parameters is the subset of points that satisfy the linear constraints. If such set does not exists, then the point estimate of θ_m is the value that minimizes the amount of violation of the inequality condition. Formally,

$$\theta_{m,s}\text{arg } \in \min \sum_{n}^{N_s} \min(0, E\left[\Delta R_n | J\right] - \theta_m)^2 \tag{23}$$

The empirical counterparts of the identification criteria is

$$\hat{\theta}_{m,s} \in \text{arg } \min \sum_{n}^{N_s} \min(0, \frac{1}{N_s}\Delta R_n - \theta_m)^2 \tag{24}$$

4 Results

4.1 Product and Store Choices

In order to predict sales and profits generated by alternative pricing decisions, I need to estimate demand. Table 4 displays the results obtained by regressing product choice probabilities on prices, Display dummies, Feature dummies, brand and package size dummies. All price coefficients are of negative sign, and feature and display dummies affect utility positively. The estimates across all categories are significant at 1% level. The regression in column i includes prices only, while columns ii also includes Display and Feature dummies. Once the two dummies are included, the price coefficients are cut substantially(except Soap and Sugar). This implies the effect on quantity sold seemingly associated with price reductions is largely driven by display and feature activities. Columns iii includes brand dummies as regressors to fully control for observed and unobserved product characteristics as in (Nevo, 2001). Though many of the brand dummies are statistically significant, it does not improve the estimation much - the coefficients are similar to those in column ii. Column iv includes both brand and size dummies. Not surprisingly, the effect of including size dummies is significant both statistically and economically. The price coefficients increase in absolute value (except Bacon, Butter and Egg). Column v shows the estimates using brand dummies and store average price as instruments, as well as size dummies as regressors. The coefficients of price in all categories are now more negative, just as the simultaneity story predicts.

The Logit estimates have implausible implications on the own elasticities, as discussed in (Berry et al., 1995) and (Nevo, 2001). 8, 7 and 12 out of the 18 categories have inelastic demand with respect to price, feature, and display, respectively. This is inconsistent with profit maximization. The Logit demand structure does not impose a constant elasticity, and therefore the estimates imply a different elasticity for each upc. Table 5 shows the mean of own-price and -promotional elasticities of each category using the estimates in column iv and v of Table 4. After instrumenting price, only 4, 4, 10 categories have inelastic demand.

Consumers usually purchase only a subset of categories at each time shopping. The fact that a category is not purchased during this week's shopping is possibly because the household still holds inventory. For goods that are considered storable, the purchase frequency largely depends on the package volume and consumption rates - purchase frequency is smaller when package volume is bigger and consumption rate is lower. Another factor that affects non-purchase would be the "attractiveness" of the category itself, which can be revealed by the percentage of households who regularly consume this category: not every household consumes ice cream, whereas most people need laundry detergent. I use an intercept χ_c to measure the intrinsic utility brought by purchasing category c. The first column in Table 7 shows the estimates of χ_c. The higher this intercept, the more likely this category is purchased, and the popular this category is among households. Therefore, a negative χ does not necessarily mean that consumers dislike the category, because the small purchase incidences could be due to its storability. The magnitude and the sign of χ also depends on other arguments that enter the utility function, including price levels and coefficients. Note that χ cannot be identified from purchase incidences but from the out-side choice (non-purchase), because it's common for all items of that category.

The store preferences are estimated using the aggregate purchase utility, home-store distances, and the average store evaluations. The out-side choice is merely no shopping or shopping at unobserved stores. Table 6 displays the estimates of store choice based on different assumptions about consumer knowledge on merchandising activities. Row i assumes that consumers have full knowledge on prices of all stores in all periods, while row ii assumes a portion ϕ_s of the population is informed by store s. The distance coefficients are negative, and the the aggregate purchase utility enters store attractiveness positively. Since row i assumes all consumers are informed, it biases the estimates of the coefficients of store attractiveness and distance. The coefficient of store attractiveness is underestimated because the additional store visits are actually generated by the proportion of ϕ_s households who are informed about price cuts and promotions. The coefficient of distance is overestimated in absolute value (more negative), as the the estimation would attribute the seemingly small effect on store traffic (because of the $1-\phi_s$ uninformed consumers) to their dislike of distance. The average store evaluation is the lowest at HT2 which has the lowest market share, and the highest at the HiLo store with the highest market share. The two high-tier stores have similar store evaluation, which is consistent with the fact that they belong to the same chain.

Using the estimates from stage 1 and 2, I am able to compute store's promotion elasticity, that is, the percentage change in the probability of choosing store s when it advertises price discount of one more item (the aggregate effect of price drop and pure promotion). This elasticity indicates how effective price promotion is in driving store traffic. The last five columns in Table 7 shows the average category elasticity across all items in that category. The last row shows the average store elasticity across all observed categories at each store. The elasticities vary largely across items(not reported), categories, and stores. On average, an additional promotion is the most effective at HiLo, and the least at HT1. All others being equal, if all consumers were informed about price information, then the store with the lowest market share should have the highest elasticity. However, the additional store visits driven by price promotion also depend on how many consumers are actually informed by ads. Price promotions are the most(least) effective at HiLo(HT1), mostly because their advertising coverage is the greatest(smallest).

4.2 Promotional Costs

The promotional costs are estimated by comparing the actual profits generated by the actual merchandising decisions, and the alternative profits led by small deviations in m^F. Therefore, the magnitude of promotional costs depend largely on the effectiveness of promotion: if store s obtains an greater increment in profits by offering one more promotion than store q, then s is able to afford higher costs in promotions. The point estimates of

θ_m consists with the theory. Table 8 shows the marginal costs (in dollars) of promotion. The 95% confidence intervals of θ_m are constructed by bootstrapping from ΔR. The point estimate and upper bound of θ_m are the highest at HiLo, implying that the HiLo store is able to afford the highest promotional expenditures. The high promotion elasticity of this store is primarily due to its large advertising coverage, therefore the increase in store profits driven by the extra promotion is high.

High promotion costs also force the store to offer deeper price discounts along with promotion. The elasticity with promotion only is not great enough to generate addition profits that could cover the marginal promotion cost. To cover this high cost, the store is more likely to offer both discount and promotion, expecting greater store visits and profits. HiLo has the greatest promotion cost, \$4.98, and 70 percent of its promotions are accompanied with deep price cuts (Table 1). In contrast, the stores with the lowest promotion costs, HT1 (\$0.97) and HT2(\$1.50), do not have to cut price much conditional on promotion. Only 28 and 34 percent of their promotions, respectively, come with deep price cuts.

The magnitude of estimated θ_m depends on the market size (see equation 11), and the estimates here are based on the observed households sampled from the area (548 in total). Therefore, the magnitude of promotional costs will be smaller if it is estimated using the information of the full population. Nevertheless, the estimates provides inference on the ratio between promotional costs and total store-level revenue, regardless of the market size. The estimates imply that the marginal cost of promotion ranges from \$0.97 to \$4.98 per promotion, and the total promotion cost comprises 3.6 to 17.1 percent of store revenues, or 10.4 to 23.7 percent of profits.

5 Conclusion

I estimate the marginal cost of feature promotion using moment inequality methods, to investigate the relationship between supermarket retails' price positioning and their tolerances on promotion costs. Both consumer and seller behaviors are of multi-category. The model is thus able to predicts the likelihoods of store visiting by offering one more (or one less) unit of price promotion. These likelihoods are used to forecast the counterfactual profits generated by alternative promotion decision. The results show that the effectiveness of price promotion varies largely by brands, categories, and stores. Moreover, due to the informing nature of price promotion, the promotion elasticity on store visits also depend on the advertising coverage of that store. Stores with larger tolerance of marginal promotion costs are those with greater advertising coverages and deeper price discounts, and are able to offer promotions on more products.

The study using multi-category profit maximization model sheds lights on the understanding of the determinants of consumer price sensitivity and the "roles" of different product categories. The structural estimates of promotion costs allows researchers to explore the rationale behind the arsenal of promotion strategies adopted by modern retailers.

References

K. Ailawadi, J. Beauchamp, N. Donthu, D. Gauri, and V. Shankar. Communication and promotion decisions in retailing: a review and directions for future research. *Journal of Retailing*, 85(1):42–55, 2009.

D. Bell and J. Lattin. Shopping behavior and consumer preference for store price format: Why "large basket" shoppers prefer edlp. *Marketing Science*, 17(1):66–88, 1998.

D. Bell, T. Ho, and C. Tang. Determining where to shop: Fixed and variable costs of shopping. *Journal of Marketing Research*, pages 352–369, 1998.

S. Berry, J. Levinsohn, and A. Pakes. Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, pages 841–890, 1995.

C. Bliss. A theory of retail pricing. *The Journal of Industrial Economics*, pages 375–391, 1988.

R. Bolton and V. Shankar. An empirically derived taxonomy of retailer pricing and promotion strategies. *Journal of Retailing*, 79(4):213–224, 2003.

R. Bolton, V. Shankar, and D. Montoya. Recent trends and emerging practices in retailer pricing. *Retailing in the 21st Century*, pages 301–318, 2010.

D. Gauri, D. Talukdar, and B. Ratchford. Empirical investigation of the impact of loss leader promotion on store and category performance in grocery industry. Technical report, Working Paper, Syracuse University, 2008.

D. Hosken and D. Reiffen. Pricing behavior of multiproduct retailers. *The BE Journal of Theoretical Economics*, 7(1), 2007.

R. Lal and C. Matutes. Retail pricing and advertising strategies. *Journal of Business*, pages 345–370, 1994.

D. Levy, M. Bergen, S. Dutta, and R. Venable. The magnitude of menu costs: direct evidence from large us supermarket chains. *The Quarterly Journal of Economics*, 112(3):791–824, 1997.

A. Nevo. Measuring market power in the ready-to-eat cereal industry. *Econometrica*, pages 307–342, 2001.

Table 1: Stage 1 - Brand Preferences

	i	ii			iii			iv			v		
Category	p	p	m^F	m^D	p	m^F	m^D	p	m^F	m^D	p	m^F	m^D
Bacon	-0.9032	-0.5551	1.1236	0.9911	-0.5217	1.1579	0.8957	-0.8038	1.0573	0.6185	-1.9291	1.2283	0.5872
	(0.2341)	(0.0235)	(0.0540)	(0.0390)	(0.0286)	(0.0570)	(0.0419)	(0.0424)	(0.0588)	(0.0469)	(0.0741)	(0.0482)	(0.0476)
Butter	-0.9129	-0.5240	1.1684	1.2192	-0.5054	1.1526	1.1866	-0.4879	1.1435	1.1582	-1.3482	1.1058	1.2899
	(0.0230)	(0.0223)	(0.0298)	(0.0284)	(0.0229)	(0.0299)	(0.0286)	(0.0285)	(0.0301)	(0.0291)	(0.0497)	(0.0377)	(0.0289)
Cereals	-0.0180	-0.0769	1.3594	0.9480	-0.2161	1.3130	0.7978	-0.2272	1.3092	0.8724	-0.4016	1.1213	0.6778
	(0.0176)	(0.0174)	(0.0556)	(0.0688)	(0.0201)	(0.0562)	(0.0696)	(0.0227)	(0.0465)	(0.0586)	(0.0391)	(0.0616)	(0.1001)
Cleansers	-0.6778	-0.4913	0.9557	0.8493	-0.4926	0.9394	0.8973	-0.9273	0.9013	0.7265	-1.7329	1.2101	0.7325
	(0.0335)	(0.0334)	(0.0514)	(0.0805)	(0.0345)	(0.0531)	(0.0812)	(0.0678)	(0.0551)	(0.0848)	(0.0227)	(0.0615)	(0.0810)
Coffees	-0.0478	-0.0029	1.5691	1.4485	-0.0073	1.5607	1.2672	-0.1940	1.3580	0.9752	-0.3928	1.1789	1.1135
	(0.0088)	(0.0091)	(0.0397)	(0.0423)	(0.0100)	(0.0407)	(0.0436)	(0.0152)	(0.0416)	(0.0463)	(0.0102)	(0.0318)	(0.0287)
Crackers	-0.4459	-0.2953	1.6941	0.8704	-0.4560	1.4467	0.5556	-0.8026	1.5336	0.7612	-1.8625	1.4362	0.7561
	(0.0284)	(0.0277)	(0.0388)	(0.0493)	(0.0344)	(0.0398)	(0.0518)	(0.0432)	(0.0329)	(0.0691)	(0.0307)	(0.0236)	(0.0329)
Detergents	-0.1273	-0.1384	1.6808	1.0894	-0.1572	1.6523	1.0627	-0.3069	1.4024	0.8965	-0.8997	1.4129	0.9105
	(0.0049)	(0.0053)	(0.0348)	(0.0434)	(0.0060)	(0.0352)	(0.0437)	(0.0149)	(0.0364)	(0.8965)	(0.0010)	(0.0032)	(0.0220)
Eggs	-1.4699	-1.0955	2.0032	1.5630	-0.3880	1.9912	1.7561	-1.0732	1.8571	1.5075	-1.1859	1.8916	1.4908
	(0.0402)	(0.0412)	(0.1689)	(0.0585)	(0.5367)	(0.1687)	(0.0595)	(0.0738)	(0.1678)	(0.0613)	(0.0498)	(0.1686)	(0.0586)
Hot Dog	-0.5138	-0.3778	1.1609	0.8919	-0.3430	1.0906	0.8218	-0.6395	0.9984	0.6394	-0.8979	1.0118	0.6982
	(0.0116)	(0.0112)	(0.0399)	(0.0286)	(0.0145)	(0.0410)	(0.0293)	(0.0215)	(0.0411)	(0.0306)	(0.0281)	(0.0438)	(0.0327)
Ice Cream	-0.7395	-0.6180	0.9821	0.6960	-0.6112	0.9972	0.5850	-0.9029	0.9349	0.3529	-1.1308	0.9972	0.7684
	(0.0202)	(0.0210)	(0.0643)	(0.0424)	(0.0229)	(0.0644)	(0.0439)	(0.0264)	(0.0647)	(0.0453)	(0.0638)	(0.0703)	(0.0430)
Nuts	-0.4397	-0.3537	1.4422	0.9202	-0.3494	1.4087	0.9283	-1.0187	1.2167	0.7213	-1.0948	1.1121	0.8724
	(0.0243)	(0.0234)	(0.0741)	(0.8818)	(0.0243)	(0.0754)	(0.0890)	(0.0297)	(0.0793)	(0.9312)	(0.0276)	(0.0673)	(0.8759)
Pizza	-0.1592	-0.1347	1.0583	1.0286	-0.1346	0.9278	1.1789	-0.6724	0.7734	0.7552	-0.6873	0.8891	0.6752
	(0.0114)	(0.0119)	(0.0401)	(0.0359)	(0.0157)	(0.0403)	(0.0365)	(0.0368)	(0.0407)	(0.0428)	(0.0109)	(0.0165)	(0.0477)
Snacks	-0.3485	-0.2372	1.4522	1.1792	-0.2627	1.4516	1.0456	-0.5471	1.6276	1.3291	-0.6928	1.7688	1.2348
	(0.0256)	(0.0255)	(0.0458)	(0.0512)	(0.0255)	(0.0482)	(0.0533)	(0.0311)	(0.0416)	(0.0313)	(0.0282)	(0.0439)	(0.0535)
Soaps	-0.2462	-0.2783	1.1905	0.9849	-0.2502	1.0857	0.9001	-0.6982	1.1275	0.8904	-0.7062	1.1283	0.6329
	(0.0169)	(0.0173)	(0.0503)	0.0725	(0.0176)	(0.0513)	(0.0732)	(0.0199)	(0.0524)	(0.0471)	(0.0122)	(0.0498)	(0.0579)
Sugar	-0.0937	-0.1537	1.3432	1.9931	-0.2344	1.1278	1.6779	-0.9092	0.7830	0.6784	-0.9827	0.8398	0.7302
	(0.0161)	(0.0174)	(0.0552)	(0.0545)	(0.0191)	(0.0558)	(0.0583)	(0.0909)	(0.0622)	(0.0663)	(0.0622)	(0.0811)	(0.0984)
Tissue	-0.7292	-0.5665	0.8383	1.2240	-0.5760	0.9033	1.1441	-0.8071	0.8576	1.0506	-0.1179	0.8727	0.1082
	(0.0137)	(0.0131)	(0.0253)	(0.0257)	(0.0140)	(0.0266)	(0.0269)	(0.0376)	(0.0268)	(0.0284)	(0.0294)	(0.0362)	(0.0291)
Towl	-0.4608	-0.2751	1.1172	1.1819	-0.3104	1.2444	1.1910	-0.9016	1.2179	1.0552	-0.9027	1.1198	1.0237
	(0.0187)	(0.0148)	(0.0272)	(0.0287)	(0.0167)	(0.0283)	(0.0297)	(0.0241)	(0.0285)	(0.0320)	(0.0297)	(0.0227)	(0.0299)
Yogurt	-0.2036	-0.1100	0.8034	1.1706	-0.1987	0.7341	1.1806	-0.2283	0.7361	1.2024	-0.2399	0.7282	1.2797
	(0.0195)	(0.0193)	(0.0564)	(0.0378)	(0.0224)	(0.0569)	(0.0387)	(0.0197)	(0.0572)	(0.0426)	(0.0200)	(0.0548)	(0.0456)

Table 2: Own-Price and -Promotion Elasticities

				IV		
Category	p	m^F	m^D	p	m^F	m^D
Bacon	-1.8336	1.0453	0.6116	-3.7682	2.0892	0.5889
Butter	-0.6550	1.1370	1.1516	-2.2668	1.2827	1.2282
Cereals	-0.2214	1.3563	0.9459	-0.4776	1.6579	1.0908
Cleansers	-1.9282	0.8986	0.7244	-3.4887	1.0908	0.9807
Coffees	-0.7066	1.3549	0.9730	-1.6463	1.2783	1.0993
Crackers	-0.8443	1.4444	0.5547	-2.9828	1.8892	0.5760
Detergents	-1.5155	1.3984	0.8940	-3.2484	1.2908	0.9087
Eggs	-1.0821	1.8177	1.4754	-1.2907	1.7668	1.6752
Hotdog	-1.8166	0.9964	0.6381	-2.7319	1.0382	0.6995
Ice Cream	-2.5993	0.9337	0.3525	-2.8709	1.1082	0.7232
Nuts	-3.0264	1.2064	0.7153	-3.2892	1.0117	0.8546
Pizza	-1.9894	0.7714	0.7532	-1.8965	0.8790	0.6884
Snacks	-0.3894	1.4503	1.0446	-0.4891	1.5748	1.0017
Soaps	-0.4911	1.0821	0.8971	-0.5092	1.0709	0.0983
Sugar	-2.9041	0.7696	0.6668	-3.0918	0.8786	0.7681
Tissue	-1.6640	0.8501	1.0414	-2.1486	0.9868	1.1376
Towl	-1.3029	1.2073	1.0460	-1.3799	1.1881	1.0091
Yogurt	-0.1893	0.7338	1.1987	-0.2001	0.8276	1.2338

The price elasticities are computed the median price of each upc. The other two elasticities are computed at that dummy equals 1.

Table 3: Stage 2 - Store Preferences

Variable	θ_u	θ_d	λ_1	λ_2	λ_3	λ_4	λ_5	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5
i	0.0065	-0.5691	0.0081	0.1881	0.4978	0.0537	0.0397	-	-	-	-	-
ii	0.0172	-0.4397	0.0068	0.1183	0.5029	0.0399	0.0301	0.0304	0.0228	0.0794	0.0117	0.0182

Table 4: Estimates of Category-Intrinsic Utility and Promotional Elasticity of Store Choice

Category	χ_c	elasticity of store choice				
		EDLP1	EDLP2	HiLo	HT1	HT2
Bacon	0.4638*	0.4047	0.5667	0.2587	-	-
Butter	-1.1447*	0.4130	0.4627	0.5016	-	0.3835
Cereals	-0.2462*	0.0513	0.1991	0.0968	0.1485	0.1643
Cleansers	-0.2291*	0.1013	0.1208	0.0840	0.0321	0.0415
Coffees	-2.7209*	0.0099	0.1743	0.2743	0.1008	0.1154
Crackers	-0.0092	0.0269	0.0316	0.0239	0.0157	0.0111
Detergents	-0.6072*	0.0667	0.4187	0.1050	0.0299	0.1003
Eggs	-1.3176*	0.0510	0.3703	0.2246	0.1565	0.2327
Hotdog	-0.0949*	0.1029	0.1332	0.0731	-	-
Ice Cream	1.1669*	0.0388	0.0097	0.0159	-	0.1120
Nuts	2.0246*	0.0527	0.1673	0.1921	0.0271	0.0361
Pizza	3.4285*	0.0682	0.0618	0.1769	0.0399	0.0712
Snacks	-1.0238*	0.0399	0.0450	0.0654	0.0732	0.0514
Soaps	-0.6679*	0.1103	0.2377	0.1425	0.0887	0.0852
Softeners	-1.7129*	-	-	2.0618	-	0.4632
Sugar	-1.6425*	0.0300	0.0113	0.0178	0.0365	0.0706
Tissue	-0.6147*	0.0480	0.2879	0.0833	0.1811	0.3730
Towl	-1.5670*	0.0607	0.3481	0.0954	0.2614	0.3355
Yogurt	-1.3485*	0.4279	0.3667	0.1090	-	0.1329
average		0.1107	0.2112	0.2422	0.0589	0.1463

"*" indicates that estimates are statistically significant at $p = 0.05$ level.
"-" indicates that the category is seldom promoted.

Table 5: Promotional Costs

Store	lower Bound	Upper Bound	95%Confidence Intervals				point estimate
			Lower Bound		Upper Bound		
EDLP1	$ 0.60	$ 1.95	$0.28	$1.04	$0.59	$3.54	$ 1.71
EDLP2	$ 0.74	$ 6.64	$0.18	$1.11	$1.02	$12.24	$ 2.31
HiLo	$ 0.79	$ 10.54	$0.26	$0.94	$2.39	$19.76	$ 4.98
HT1	$ 0.14	$ 1.81	$0.08	$0.18	$0.60	$2.83	$ 0.97
HT2	$ 0.47	$ 2.57	$0.14	$1.14	$0.80	$4.48	$ 1.50