A Nested Logit Model of Strategic Promotion

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by

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Abstract:

Retailers use sales – price promotions – for a number of potential reasons. There is relatively little research, however, on their strategic role among frequently consumed perishable products. Using a two-stage, nested logit model of retail equilibrium, we show that promotion will be most effective (ie. increase store-level sales) if products are highly differentiated, but stores are relatively similar. To test this hypothesis, we an oligopolistic model of promotion rivalry with category-level scanner data from the four largest supermarket retailers in a major U.S. metropolitan market. The results show that promotion has a greater impact on store share than product share, because the elasticity of substitution among stores is larger than the elasticity of substitution among products. Consequently, promotion has its greatest value in driving demand for differentiated products among stores that are similar. This finding supports the observed trend toward premium private label products being offered by supermarket retailers.

Key words: game theory, nested logit, product differentiation, promotion, retailing, strategic marketing.

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A Nested Logit Model of Promotion Rivalry

Introduction

Promotion, defined as a temporary reduction in price, now accounts for the majority of food retailers' marketing budgets. Despite the ubiquitous nature of retail price promotions – sales – there is little common understanding among economists as to why supermarket retailers occasionally offer products at discounted prices, or even how such price dispersion can exist as an equilibrium phenomenon. Understanding how and why price promotions "work" is critically important not only for retailers, but all others interested in the competitiveness of the retail sector. With increasing concentration in virtually all markets, it may be the case that sales play a strategic role among oligopolistic supermarket chains. This paper examines whether this is indeed the case using a somewhat novel nested logit modeling approach.

There are many explanations for why retailers use sales. Varian (1980) describes a simple model of monopolistically competitive equilibrium in which sales are the outcome of a mixed strategy equilibrium among retailers who compete over cohorts of relatively informed and uninformed consumers. Defining these cohorts as market segments consisting of loyal or non-loyal consumers, Narasimhan (1988) characterizes competitive promotional strategies by their depth and frequency within a mixed strategy equilibrium framework similar to Varian (1980). Pesendorfer (2002) extends this logic to a specific consumer packaged goods case in which retailers price discriminate over time, between loyal and non-loyal consumers. Intertemporal price discrimination, however, requires the products themselves to be storable and infrequently purchased so that consumers are able to wait for the next sale to occur. Neither of these conditions apply to perishable products such as fresh fruits and vegetables or dairy products that are frequently purchased and are not easily stored for long periods of time. Further, both Varian (1980) and Pesendorfer (2002) assume retailers sell only a single product whereas supermarkets typically offer hundreds of products on promotion each week out of thousands available on their shelves. Hess and Gerstner (1987), Bliss (1988), Epstein (1988), Lal and Matutes (1995), McAfee (1995) and Hosken and Reiffen (2001) explicitly allow for multiple-product interactions in which loss-leadership emerges as the dominant rationale for price promotions. Their models, however, describe either a competitive retail sector in which sellers take others' prices as given, or monopoly sellers that have no need to consider rivals' reactions.

Because price promotion now dominates most suppliers' marketing budgets, it is somewhat surprising that there is little research on the strategic role of price promotion. Although there is a large amount of work in the empirical marketing literature (Gupta, 1988; Nijs, et al. 2001; Pauwels, et al. 2002) that investigates the differential role of price promotion in driving purchase incidence, category choice and brand choice, the models that are used typically consider only the demand-side of the market and not strategic interactions among firms. With local retail markets becoming increasingly concentrated, it is more likely that the effectiveness of price promotion as a marketing tool depends on the reactions of rival firms to discounting strategies.

Economists have also developed a range of demand-side empirical models designed to determine how sales "work." Hendel and Nevo (2002) estimate a dynamic model of consumer stockpiling and sales, but focus on the household-level problem and do not consider the firm's decision. Moreover, stockpiling is not an option with most of the perishable products that dominate retailers' "food page" ads on a weekly basis. Porter (1983) applies the trigger price model of Green and Porter (1984) to explain discontinuous price paths among 19^{th} century railroads. In this model, temporary price reductions are interpreted as punishments intended to reinforce a tacitly collusive oligopoly outcome. Slade (1987), on the other hand, regards price wars more as information gathering devices in which rival sellers discover each others' costs by deeply discounting prices for short periods of time. Supermarket retailers have very similar costs, however, and sell many products simultaneously so single-dimension price wars are not likely to provide the same type of information gained by the gas stations described by Slade (1987).

For promotion to be effective from a retailer's perspective, discounting prices must increase store traffic and not simply reallocate demand among products sold within the store (Chintagunta, 2002). Whether promoting one product cannibalizes sales from another in the store or attracts customers from another retailer depends critically upon the elasticity of substitution among products within the store relative to the elasticity of substitution among stores. Which elasticity is greater is of some question. Slade (1995) argues, and provides some limited empirical evidence, that consumers shop only among products within a store that is chosen according to some other criterion. Anderson and De Palma (1992), on the other hand, suggest that if products at one location are intended to satisfy diverse needs, then the elasticity of substitution among them is likely to be quite low. To answer this question, we use a modeling procedure capable of estimating both store and product heterogeneity – the nested logit – as the basis for a structural model of equilibrium in a particular retail market.

The primary hypothesis that we seek to test in this paper is that promotions for perishable products are critical strategic tools used by supermarket retailers. The objective of this study is to test whether supermarket retailers in a specific geographic market use price promotions (both in terms of the size of the discount and the number of products offered) in a strategic way – to gain market share and pricing power over rival stores. The paper begins by presenting an empirical model of consumer demand, sale pricing and promotional breadth based on the variance components nested logit of Cardell (1997) and Berry (1994). The third section describes the data and specific methods used to estimate the structural model, including the instruments employed and the way in which we account for the mixed strategy nature of sales. A fourth section presents and interprets the estimation results and draws several implications for the nature of strategic rivalry in the retail supermarket industry. The final section concludes.

Economic Model of Sales

Overview

Retailers are assumed to behave as if they follow a two-stage price-promotion decision process. In the first stage, they decide whether to offer a promotion during a particular week for each product. This decision depends on wholesale prices, previous retail prices, and the number of products offered for sale in the previous period. Conditional on the decision to offer a product on sale, retailers then decide the specific price and number of products to offer for sale in the second stage. Retailers choose sale prices and the number of products to put on sale in order to maximize store profit. Because both variables at this stage are necessarily endogenous when retailers behave strategically, prices and the number of sale products will be correlated with the errors in the demand equation. Following Villas-Boas (1999), Chintagunta (2002) and others, therefore, we model the endogeneity of each decision by estimating price and sale product number equations simultaneously with demand. As a result, the second-stage empirical model consists of three equations: (1) demand, (2) price response and (3) the number of sale products. Each includes a correction factor for the endogenous first-stage sale decision in a generalized Heckman framework.

The Sale Decision

The variables used in the probit model are based on previous theoretical and empirical models of promotion frequency. First, promotion activity is likely to vary by product and store, so the model is estimated allowing for fixed effects in both dimensions. Second, many authors find that retail prices tend to fall during periods of peak demand, because competition is most intense when shopping behavior is likely to provide the greatest benefit (Warner and Barsky, 1995; Lach and Tsiddon, 1996; MacDonald, 2000; Chevalier, Kashyap and Rossi, 2000). Consequently, the probability that a product is offered on sale in a given week is a function of binary seasonal indicator variables. Third, discounts are also likely to be driven by variation in wholesale prices (Hosken and Reiffen, 2004). While suppliers of consumer packaged goods often provide retailers incentives to promote their products by temporarily reducing wholesale prices, or by providing off-invoice allowances, cost-driven sales of fresh produce items are more likely to reflect competitive market factors. Typically, retail prices for fresh produce do not follow wholesale prices downward instantaneously, however, so we use lagged wholesale prices to reflect the observed asymmetry of retail price adjustment (Ward, 1982; Pick, Karrenbrock and Carman, 1990; Powers, 1995). Fourth, the probability that a frequently-consumed product is offered on sale increases in the time since the last sale (Pesendorfer, 2002). While this effect is more likely to be true for storable products, or those for which purchases can be delayed, many of the fresh fruits considered here are not "perfectly perishable" in the sense that they must be consumed within a few days of purchase. Apples, grapes and oranges can often be stored for more than one week before being consumed. Therefore, we also include lagged retail prices to account for those consumers who are able to postpone their fruit purchases until the next sale. Finally, McAfee (1995) shows that the probability of a sale by a multi-product retailer depends on the number of products offered for sale. Because there is likely to be diminishing marginal benefits to the number of products offered on discount during any given week, we expect the probability of a sale to fall in the number of products offered for sale in the current week.

Including each of these factors in a vector z, define the unobserved marginal benefit to placing an item on sale as: $d^*_{ijt} = \gamma' z + \epsilon_1$. Assuming the error term is normally distributed, the first-stage probit model is written:

$$Pr[d_{ijt} = 1] = Pr[d^*_{ijt} > 0] = Pr[\epsilon_1 < \gamma' z] = F(\gamma_0 + \sum_j \gamma_{1j} c_j + \sum_i \gamma_{2i} h_i + \sum_k \gamma_{3k} b_k + \gamma_4 r_{i,t-1} + \gamma_5 n_{i,t-1} + \gamma_6 p_{ij,t-1}), \quad \textbf{(1)}$$

where d_{ijt} is a binary variable that equals 1 when product i in chain j is offered on promotion during week t, n_{jt} is the number of products offered on discount by chain j during week t, r_{it} is the wholesale price of product i in week t, c_j is a set of chain-indicator variables, b_k is a set of k seasonal binary variables, h_i is a set of product-specific binary variables, γ is a vector of parameters and F is the standard normal distribution function. Equation (1) is easily estimated using maximum likelihood methods. Using the estimated γ values from this equation, the predicted probability of a sale is given by: $\hat{d}_{ij} = F(\hat{\gamma}^{\prime} z)$. The fitted sale probability is then substituted into the demand model described next in order to account for the endogeneity of d_{ij}, the sales decision. In this way, we ensure that the remaining parameters are consistently estimated.

Demand

Retail demand for fresh produce derives from a random utility framework. Mean utility for consumer h from consuming good $i \in I$ purchased in store $j \in J$ is a function of the shelf price (p_{ij}), the number of products offered for sale, the total number of distinct products on the shelf (a proxy for variety), m_j, the predicted probability of a sale, and an interaction term between the predicted sales dummy and the sale price. Utility, therefore, is written as:

$$u_{ijh} = x_{ij}^{\prime}\beta - \alpha p_{ij} + h(n_j) + \eta_{1ij} + v_{hj} + (1-\sigma_J)v_{ih} + (1-\sigma_I)(1-\sigma_J)\epsilon_{ijh}, \qquad \textbf{(2)}$$

where η_{1ij} is a random error that is unobserved by the econometrician, but reflects variables known to the firm that influence the product's price: shelf space, supplier rebates, anticipated shortages and the like and $\boldsymbol{x}$ is a vector of all covariates other than price and the number of sale products, including fixed product and store effects. The number of sale products, n_j, is a direct argument of the utility function because consumers are better able to find their preferred product on sale the more products retailer j offers on promotion (McAfee, 1995). Further, consumer research shows that shoppers prefer stores that often many products on sale at any given time, even when the total cost of their purchase is similar to other stores that follow a more distinct, HI-LO strategy (Food Marketing Institute). Thus, consumers experience a "second order" effect of sales in addition to the lower cost that they imply.[2] Including an interaction term allows for the possibility that items on promotion become less elastic if consumers perceive discounting as a means of differentiating otherwise similar products. Consumers are assumed to have diminishing marginal utility for the number of sale products, so the sales-utility function in (2) is written: $h(n_j) = \rho_1 n_j + \rho_2 n_j^{1/2}$.

The demand system implied by (2) is derived using an extension of the variance component formulation of Cardell (1997), Berry (1994) and Currie and Park (2003) with three nesting levels: (1) the choice of the "outside option" (no purchase), (2) the choice of store (group of products), and (3) the choice of product conditional on store choice. Cardell (1997) defines the distribution of v_{ih} as the particular distribution that causes the term (v_{ih} + (1 - σ_I)ϵ_{ijh}) to be extreme-value distributed if the household specific error term ϵ_{ijh} is itself extreme-value distributed. Extending this logic to a second nesting level implies that v_{hj} also possess the unique distribution that causes $v_{hj} + (1 - \sigma_J)\, v_{ih} + (1 - \sigma_I)\,(1 - \sigma_J)\epsilon_{ijh}$ to be extreme-value distributed. The parameters σ_J and σ_I are interpreted as measures of store and product heterogeneity, respectively such that $0 \leq \sigma_K \leq 1$ for $k = I, J$. Clearly, if $\sigma_J = 1$, then the correlation among stores goes to 1.0 and stores are regarded as perfect substitutes, or if $\sigma_I = 1$, then products within each store are perfect substitutes. On the other hand, if these parameters each are zero, then the model collapses to a simple multinomial logit model, without store or product nests. Notice that, by

[2] Pauwels, et al. (2002) outline a number of other ways in which promotion increases demand independent of the price effect. Impulse buying, stockpiling, purchase acceleration, learning and reinforcement are all ways in which promotions can increase demand independent of the pure price effect.

including an outside option, we are able to test whether sales have any general demand-expansion effects or if they merely reallocate demand among products within a store, or among stores.

Based on the random utility model in (2), define the level of mean utility for each choice of product *i* and store *j* as: $\delta_{ij} = x_{ij}\beta - \alpha p_{ij} + h(n_j) + \eta_{1ij}$. The log-sum, or inclusive value, for the choice among products conditional on store choice (nesting level (3) above) is found by adding the utility from all products in a particular store according to:

$$E_I = \sum_{i \in I} e^{\delta_{ij}/(1-\sigma_J)(1-\sigma_I)}, \tag{3}$$

so the conditional share of product *i* given that the consumer buys from store *j* is given by:

$$s_{i|j} = \frac{e^{\delta_{ij}/(1-\sigma_I)(1-\sigma_J)}}{E_I}. \tag{4}$$

At the second nesting level, a consumer's utility reflects the choice of one store from among *J* alternatives, conditional on the consumer actually going to a supermarket rather than a farmers market, convenience store or any one of a number of alternatives. The market share of each store, therefore, is written as:

$$s_{j|J} = \frac{E_I^{1-\sigma_I}}{\sum_{I \in J} E_I^{1-\sigma_I}} = \frac{E_I^{1-\sigma_I}}{D_J}, \tag{5}$$

where the inclusive value term for the conditional store choice is: $D_J = \sum_{I \in J} E_I^{1-\sigma_I}$. At the uppermost level, or the choice between buying fruit from a supermarket and some other outlet, category share is given by the equation:

$$s_J = \frac{D_J^{1-\sigma_J}}{1 + \sum_J D_J^{1-\sigma_J}}. \tag{6}$$

where the denominator reflects the existence of a viable outside option to all elements of *J*. Combining each of the component market shares, the marginal share of product *i* purchased in store *j* is the product of the conditional share of product *i* given that a purchase was made from store *j*, the conditional share of store *j* given that the purchase was made from a supermarket, and the share of all supermarkets in the total market:

$$s_{ij} = (s_{i|j})(s_{j|J})(s_J) = \frac{e^{\delta_{ij}/(1-\sigma_J)(1-\sigma_I)}}{E_I^{\sigma_I} D_J^{\sigma_J}(1 + \sum_J D_J^{1-\sigma_J})}, \quad i = 1,2,...I, \quad j = 1,2,...J. \tag{7}$$

where the utility of the outside option, or no purchase, has been normalized to zero. Taking logs of both sides of (8) leads to a share equation for product *i* in store *j* that is a function of the unobservable inclusive values:

$$\ln s_{ij} = \delta_{ij}/(1-\sigma_I)(1-\sigma_J) - \sigma_I \ln(E_I) - \sigma_J(D_J) - \ln(1 + \sum_J D_J^{1-\sigma_J}), \tag{8}$$

and substitution parameters at the product and store-levels. Substituting expressions for the aggregate supermarket share in (6) and the store (or more accurately, supermarket chain) share in (5) into equation (8) and simplifying gives the marginal share of product *i* in store *j*:

$$\ln s_{ij} - \ln s_0 - x_{ij}^{/}\beta + \alpha p_{ij} - h(n_j) - \sigma_J \ln(s_{j|J}) - \sigma_I(1-\sigma_J)\ln(s_{i|j}) = \eta_{1ij}, \tag{9}$$

where η_{1ij} is the econometric error term described in (2) above. Equation (9), however, cannot be estimated using ordinary least squares because η_{1ij} is likely to depend on other elements in δ_{ij}. In other words, sales strategies, both in terms of the number of goods offered for sale and the depth of discount, are assumed to be endogenous. The next section describes how we estimate the parameters of (9) when the variables of interest are endogenous.

Retailer Price and Promotion Decision

Villas-Boas and Winer (1999) show that demand estimates will be biased and inconsistent if such endogeneity is not properly addressed. As in Berry (1994), Chintagunta (2002) and others, we account for the endogeneity of price promotions by estimating (9) along with first-order conditions for a Nash equilibrium in sale prices and sale-product numbers in a structural model of retail demand and supply. Supermarket retailers are assumed to maximize profits on a category-basis. Interviews with several supermarket managers suggest that chain-wide pricing authority tends to rest with managers who are given pricing authority over whole categories such as dairy, meat or beverages. In the current example, this assumption means that the profit maximization problem involves setting simultaneous sales strategies for all products in the fresh fruit category. Therefore, the profit equation for retailer *j* is written as:

$$\Pi_j = Q\sum_{i\in I}(p_{ij} - c_{ij})s_{ij} - g(n_j), \tag{10}$$

where Q is the size of the total market, c_{ij} is the marginal cost of selling item *i* in store *j*, and g (n_j

) is the cost of mounting a sale, including shelving costs, labeling costs, and the cost of featuring the item in a food-page ad. Marginal selling costs are assumed to be separable between the wholesale cost of purchasing inventory, r_{ij}, and the cost of operating the store. The marginal cost function is derived from a Generalized Leontief cost function $C(\boldsymbol{w}, \boldsymbol{q})$ that specifies total store costs as a function of a vector of outputs ($\boldsymbol{q}$) and a vector of input prices ($\boldsymbol{w}$). Outputs consist of the volume sales of each item in the fresh fruit category, while input prices include prices of labor, energy and marketing services. Therefore, the marginal cost function is written as:

$$c_{ij} = r_{ij} + \sum_k \tau_k w_k + \sum_k \sum_l \tau_{kl} (w_k w_l)^{1/2}, \qquad \textbf{(11)}$$

where τ_k are parameters to be estimated and $c_{ij} = \partial C_{ij} / \partial q_{ij}$. Price promotion also implies a cost in addition to the discount itself. Direct economic costs of announcing the promotion, changing shelf-prices, or setting up a display are likely to be relatively small (Levy, et al., 1997), while indirect costs associated with customer alienation or confusion (Blinder, et al., 1998) may be many times larger. Because promotional costs are assumed to be convex, we write the cost function g similar to Draganska and Jain (2003):

$$g(n_j) = \lambda_0 + \lambda_1 n_j + \lambda_2 n_j^2, \qquad \textbf{(13)}$$

so the marginal cost of promotion is a linear function of the number of products offered for sale. Each retailer is assumed to maximize profits from all products in the category simultaneously. This is consistent with the practice of category management now used by a majority of supermarket retailers and implies that managers, at least implicitly, take into account all of the cross-price effects that are involved in setting the price for any single product. Adopting a portfolio effect to pricing means that retailers internalize any local monopoly power they may have over shoppers who have committed to their store (Bliss, 1988; Nevo 2001). Consequently, the first order conditions for the manager of store *j* are written in general form as:

$$\frac{\partial \Pi_j}{\partial p_{ij}} = Q s_{ij} + Q \sum_k \Omega_{ik} \frac{\partial s_{kj}}{\partial p_{ij}} (p_{kj} - c_{kj}) = 0, \quad i = 1,2,\ldots m, \tag{14}$$

with respect to price, where Ω is a matrix with $\Omega_{ik} = 1$ if *i* and *k* are two products sold by the same firm, and $\Omega_{jk} = 0$ if not (Nevo, 2001). In this way, (14) captures the essential multi-product nature of retailing while allowing for a general pattern of product interactions in $\partial s_{kj} / \partial p_{ij}$.

Similarly, the first-order condition with respect to the number of sale products offered in the same category as product *i* is:

$$\frac{\partial \Pi_j}{\partial n_j} = Q \sum_k \Omega_{ik} \frac{\partial s_{kj}}{\partial n_j} (p_{kj} - c_{kj}) - \frac{\partial g_j}{\partial n_j} = 0, \quad i = 1,2,\ldots m, \tag{15}$$

Retailers are assumed to solve the first order conditions in (14) and (15) simultaneously. Therefore, the solution is simplified considerably by writing each in matrix notation:

$$Q\boldsymbol{s} + Q(\boldsymbol{\Omega}\nabla_p)(\boldsymbol{p} - \boldsymbol{c}) = 0, \tag{16}$$

with respect to price, and:

$$Q(\boldsymbol{\Omega}\nabla_n)(\boldsymbol{p} - \boldsymbol{c}) - \nabla_g = 0, \tag{17}$$

with respect to the number of products offered for sale where ***s*** is a vector of market shares for all

m products, $\boldsymbol{p}$ is a vector of prices, $\boldsymbol{c}$ is a vector of marginal costs, ∇_{p} is a matrix of price derivatives with typical element: $\partial s_{kj}/\partial p_{ij}$, ∇_{n} is a matrix of sale-product derivatives with typical element: $\partial s_{kj}/\partial n_j$, and ∇_{g} is a matrix of marginal-promotion cost functions with element: $\partial g_j/\partial n_j$. Solving for ($\boldsymbol{p}$ - $\boldsymbol{c}$) and substituting into (17) yields an estimable form of the structural model with margins and the number of sale products as endogenous left-side variables and market shares, market size and response parameters on the right-side:

$$(\boldsymbol{p} - \boldsymbol{c}) = -(\boldsymbol{\Omega}\nabla_p)^{-1}\boldsymbol{s}, \tag{18}$$

for the retail margin, and:

$$\nabla_g = -Q(\boldsymbol{\Omega}\nabla_n)(\boldsymbol{\Omega}\nabla_p)^{-1}\boldsymbol{s}, \tag{19}$$

for the number of sale products. Before (19) and (20) can be estimated, however, it remains to derive the specific form of ∇_{p} given the nature of the game played among retailers.

In the empirical application below, we define eight different products in four stores in the Los Angeles market. If we were to allow for general Nash behavior with respect to all products, the problem quickly becomes intractable as there would be a total of 32 different store-products. Therefore, we simplify the supply side considerably by assuming a common response across all products by one store manager with respect to the basket of products offered by each of the other three. In other words, a manager is implicitly assumed to form only three unique expectations of how other stores' average prices will change in response to his or her own prices, rather than 24 different conjectures. This assumption not only simplifies the empirical model, but is more realistic as well. Survey evidence by McLaughlin, et al. (1999) suggest that store managers tend to set prices based on their assessment of category-level prices set by competitors in the same market. While a simplification, allowing for Nash behavior in this way is more general than the Bertrand-Nash assumption maintained by Draganska and Jain (2003), Besanko, Gupta and Jain (1998) or Nevo (2001). In the empirical application below, we test for whether Bertrand-Nash pricing and sale-product numbers are more appropriate than the associated CV solution.

The general Nash model is derived by allowing for non-zero price and sale product-responses across stores. In each case, the response parameter is identified by including the cross-price or cross-product derivative in the ∇_p and ∇_n matrices defined above. For example, the typical element of ∇_p in the general model is

$$\nabla_p^{ij} = \partial s_{i,j} / \partial p_{i,j} + \sum_{-i \in I} \sum_{-j \in J} (\partial s_{-i,-j} / \partial p_{-i,-j}) \phi_{i,j}, \quad \textbf{(20)}$$

where $\phi_{i,j} = \partial p_{-i,-j} / \partial p_{i,j}$ for all other products in all other stores and similarly for the sale-product derivative matrix where the typical element is:

$$\nabla_n^{ij} = \partial s_{i,j} / \partial n_{i,j} + \sum_{i \in I} \sum_{-j \in J} (\partial s_{-i,-j} / \partial n_{-i,-j}) \pi_{i,j}, \quad \textbf{(21)}$$

and $\pi_{i,j} = \partial n_{-i,-j} / \partial n_{i,j}$. Applying these derivatives to the marginal share equation in (8) gives expressions for the matrix of price responses in terms of the parameters of the nested logit model:

$$\begin{aligned} \nabla_p^{i,j} = \left(\frac{\alpha}{(1-\sigma_I)(1-\sigma_J)} \right) & s_{i,j} [(1 - \sigma_I s_{i|j} - \sigma_J (1-\sigma_I) s_{j|J} s_{i|j} - (1-\sigma_I)(1-\sigma_J) s_{i,j}) \\ & - \sum_{-i \in I} \sum_{-j \in J} \phi_{i,j} (-\sigma_I s_{-i|-j} - \sigma_J (1-\sigma_I) s_{-j|J} s_{-i|-j} - (1-\sigma_I)(1-\sigma_J) s_{-i,-j})], \end{aligned} \quad \textbf{(22)}$$

for all products, i, and stores, j. Substituting (22) into (18) and adding an econometric error term, the margin for product i in store j in general Nash rivalry is:

$$p_{i,j} - c_{i,j} - \left(\frac{(1-\sigma_I)(1-\sigma_J)}{\alpha}\right) / [(1-\sigma_I s_{i|j} - \sigma_J(1-\sigma_I)s_{j|J}s_{i|j} - (1-\sigma_I)(1-\sigma_J)s_{i,j}) \\ - \sum_{-i\in I}\sum_{-j\in J}\phi_{i,j}(-\sigma_I s_{-i|-j} - \sigma_J(1-\sigma_I)s_{-j|J}s_{-i|-j} - (1-\sigma_I)(1-\sigma_J)s_{-i,-j})] = \eta_{2j}, \tag{23}$$

for all products, i, and retailers, j. Substituting this expression into the solution for the optimal number of sale products yields:

$$\lambda_1 + 2\lambda_2 n_j - \frac{1}{\alpha}Q(s_{i,j} + \sum_{-i\in I}\sum_{-j\in J}\pi_{i,j}s_{-i,-j})(\rho_1 + \tfrac{1}{2}\rho_2 n_j^{-1/2}) = \eta_{3j}, \tag{24}$$

where η_{2j} and η_{3j} are both identically, independently distributed error terms. The full second-stage model, therefore, consists of equations (9), (23) and (24). These equations are estimated simultaneously using an instrumental variables method described in greater detail below.

Heterogeneity and Promotion Effectiveness

What are the implications of Nash rivalry for whether price-promotion increases category, chain or product sales? In this section, we determine the linkage between heterogeneity at the store- and product-level and the impact of price-promotion in an analytical way, while the next section does so empirically. In recent years, retailers have embarked on a number of efforts designed to differentiate themselves from rivals on a store-level through alternative store formats, signage, value-added services, or customer service. Similarly, there is a growing trend among retailers to achieve a high degree of product-level differentiation through offering their own private-labels, or stocking locally produced or unique items that others may not. Although there are many different ways of defining the "effectiveness" of a temporary price reduction, we are concerned with the impact of a sale on the contribution to store profit from the sale of a representative product, *i*.[3] If we convert equation (23), it is straightforward to show that margins vary inversely with the elasticity of demand, as is usually the case. Baker and Bresnahan (1985) and Werden (1998) show that the appropriate measure of demand elasticity is the total, or "residual" demand elasticity that takes into account competitive responses to a firm's change in its own price. In our application, the total elasticity of demand consists of four parts: (1) the elasticity of product-demand conditional on the choice of a particular store ($\theta_{i|j}$), (2) the elasticity of store-demand conditional on having purchased and inside-good ($\theta_{j|J}$), (3) the elasticity of inside-good demand (θ_J), and (4) the response elasticity of rival-product sales ($\Phi_{i,j}\theta_{-i,-j}$) where:

$$\theta_{i,j} = \theta_{i|j} + \theta_{j|J} + \theta_J + \sum_{-i \in I} \sum_{-j \in J} \Phi_{i,j}\theta_{-i,-j}, \tag{25}$$

where Φ_{ij} is the response-elasticity: $\Phi_{ij} = \phi_{ij}(p_{-i,-j}/p_{i,j})$ for each product *-i* in all other stores, *-j* (Baker and Bresnahan, 1985). Examining each of these elasticities individually shows the effect of product and store heterogeneity on the distributional effect of a price-promotion across product share, category share and store share.

Based on the demand system in (9), we calculate own- and cross-price elasticities both within and among stores for all products. Expanding each component of (25), the own-price

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[3] The random utility model includes three promotion-related effects: (1) an increase in utility from paying a lower price, as measured by the price elasticity, (2) a shift in demand due to the announcement effect, measured by a binary "sales" indicator variable, and (3) a rotation of the demand curve, estimated through an interaction term between the binary sale and continuous price variables. To ensure that the econometric model remains tractable, we account for the endogeneity of all three effects, but include only the continuous price effect in the promotion-impact calculations. This method captures the effect that is of greatest interest to retailers.

conditional product elasticity for product *i* in store *j* is given by:

$$\theta_{i|j} = \left(\frac{\partial s_{i|j}}{\partial p_{i,j}}\right)\left(\frac{\bar{p}_{i,j}}{\bar{s}_{i|j}}\right) = \bar{p}_{i,j}\left(\frac{\alpha}{(1-\sigma_I)(1-\sigma_J)}\right)(1-\bar{s}_{i|j}), \quad \textbf{(27)}$$

while the price elasticity of conditional store choice is:

$$\theta_{j|J} = \left(\frac{\partial s_{j|J}}{\partial p_{i,j}}\right)\left(\frac{\bar{p}_{i,j}}{\bar{s}_{j|J}}\right) = \bar{p}_{i,j}\left(\frac{\alpha}{(1-\sigma_J)}\right)\bar{s}_{i|j}(1-\bar{s}_{j|J}), \quad \textbf{(28)}$$

and the price elasticity of category choice becomes:

$$\theta_J = \left(\frac{\partial s_J}{\partial p_{i,j}}\right)\left(\frac{\bar{p}_{i,j}}{\bar{s}_J}\right) = \alpha\bar{p}_{i,j}\bar{s}_{i|j}\bar{s}_{j|J}(1-\bar{s}_J), \quad \textbf{(29)}$$

and, finally, the cross-price elasticity for product *i* in store *j* with respect to all other products -*i* in other stores -*j* is given by:[4]

$$\theta_{-i,-j} = \bar{p}_{-i,-j}\left(\frac{\alpha}{(1-\sigma_I)(1-\sigma_J)}\right)[-\sigma_I\bar{s}_{-i|-j} - \sigma_J(1-\sigma_I)\bar{s}_{-i|-j}\bar{s}_{-j|J} - (1-\sigma_I)(1-\sigma_J)\bar{s}_{-i,-j}], \quad \textbf{(30)}$$

where each elasticity is evaluated at the mean price and market, store and product share. Based on these expressions, we form hypotheses as to the expected effect of product and store heterogeneity on the overall elasticity of price-promotion.

[4] While the cross-price elasticities also consist of product, store and category components, we simplify the response-estimation procedure by using the partial cross-elasticity. Little additional information is gained by estimating responses to each cross-elasticity component.

First, the elasticity of product-share conditional on store-choice falls in the degree of heterogeneity among both products and stores. This is to be expected as a price reduction will be more likely to draw sales from other products within the same store, and customers from other stores, the higher the elasticity of substitution at each level. Second, the elasticity of conditional store-choice is independent of the degree of product heterogeneity, but falls with store differentiation. Again, this result is straightforward because the only way retailers can expand share among consumers who have already decided to buy from one of the major retailers is to earn share from one of the other stores. Their ability to do so is limited by the extent to which each store has developed a strategy designed to match the preferences of consumers in a particular target market. Third, the elasticity of category choice depends only on share and not on either differentiation measure. This is the standard logit result at the primary nesting point. Finally, the gross cross-price effect depends on product and store-differentiation in a similar way to the own-price effect, but opposite in direction. Specifically, if a competing store offers a promotion in a given week, the impact on the overall market share of another store will be higher the greater the elasticity of substitution among their products, and among the stores themselves. The net effect, however, depends upon the sign and magnitude of the estimated response, or conjectural elasticity. If this elasticity is positive, then a promotion by one store leads to a similar promotion by another and destructive price competition ensues. If the response elasticity is negative, however, a promotion will elicit an opposite response by the other firm and a Cournot-like outcome will be the result. Which of these effects is closer to reality is an empirical question.

Estimation Method

In the general Nash model defined above, each market share, number of sale products and price variable is assumed to be endogenous. Consequently, we estimate the entire system using an instrumental variables approach, specifically non-linear three stage least squares (NL3SLS). Unlike Draganska and Jain (2003), the retail demand variables are not suitable instruments in our problem because they are likely to be correlated with the demand-equation errors. Therefore, we use all of the explanatory variables in the model that are likely to be truly exogenous: input prices, wholesale fruit prices, and exogenous demand variables. Because this set of instruments is too small to identify the entire set of parameters, we exploit the panel nature of the data set to add more information. Specifically, cost is likely to vary among stores so we use a set of store and product dummies as well as interaction terms between input prices and the store-product binary variables as additional instruments. Villas-Boas (2003) as well as Draganska and Jain (2003) use a similar approach in constructing GMM estimators for linearized logit demand systems.

Typically, structural models of pricing behavior are assumed to represent pure-strategy equilibria because response parameters are not random. Many authors have shown, however, that sales can only exist as equilibrium phenomena among multi-product retailers if each is assumed to play a mixed-strategy in output prices (Varian, 1980; MacAfee 1985). Therefore, the empirical model describes a mixed-strategy equilibrium by treating promotions as discrete, endogenous events. As explained above, estimating an empirical mixed strategy equilibrium requires a two-stage estimation procedure. The first-stage univariate probit model is estimated using maximum likelihood techniques, while the second stage NL3SLS procedure includes the estimated sale-probabilities as a regressor in place of the endogenous sales binary variable (Heckman, 1978). As is well understood, using an estimated regressor in the second-stage regression causes the standard errors in the structural model to be biased and inconsistent. Therefore, we employ the Murphy and Topel (1985) correction method. Accounting for promotions in this way ensures consistent tests of our primary hypotheses regarding retailer pricing and sale behavior.

Data and Methods

The primary data for this study consist of two years of weekly retail scanner data from January 1998 through December 1999 for the four major chains in the Los Angeles market. The data measure specific product-level (price-look up, or PLU code-level) price, quantity and promotional activity for bananas, apples, grapes and fresh oranges aggregated to the chain-level from all stores in each chain for the Los Angeles market. All scanner data are supplied by Fresh Look Marketing, Inc. of Chicago, IL.

This data set is valuable for its focus on fresh produce and the unique attributes of the Los Angeles market. Both provide a number of advantages over more usual retail scanner data sets. First, pricing decisions for fresh produce are not dependent upon contractual arrangements between retailers and suppliers that, in the consumer packaged goods market, often reflect manufacturer promotions, rebates, slotting allowances, minimum prices or extensive forward buying. Second, fresh produce is typically not subject to inventory accumulation by consumers so promotions do not simply accelerate planned purchases to the same extent as discounts on storable products (Pesendorfer 2002). Third, the supply sector for fresh produce is relatively competitive when compared to the largely bilateral monopoly that exists in consumer packaged goods. Los Angeles is an ideal market to study retail pricing by traditional supermarkets because the four leading chains (the ones chosen for this study) all follow HI-LO pricing strategies, they all have similar shares of the fresh produce market, they are all geographically dispersed throughout the greater Los Angeles area, and perhaps most importantly, Wal Mart is not a factor in the Los Angeles grocery industry. This final point is important because Wal Mart does not participate in any national data syndication efforts so any retail scanner data set for any other market is necessarily missing data for one important player. Data for each type of fruit are disaggregated into two sub-products: the dominant PLU and all other PLUs. In this way, we account for all category volume and yet capture the effect of price promotions offered on the major item. For each product, a price promotion is defined as a reduction in price greater than or equal to 5% from the previous week's average selling price. Hendel and Nevo (2002) use a similar sale definition and find little difference between this and other discount-thresholds. Wholesale prices are obtained from either the Washington Growers Clearing House (apples), National Agricultural Statistics Service - USDA (grapes and oranges) or the International Monetary Fund (bananas) and represent average FOB shipping-point prices across all sizes and grades. Input prices include three indices of wages paid in the food-retail sector (Bureau of Labor Statistics) and fixed costs such as energy, marketing services and finance, insurance and real estate services (Bureau of Labor Statistics). All wholesale prices are available on the same, weekly basis as the retail data, but input prices are monthly. We convert the monthly data series to weekly data by first setting each weekly observation equal to the relevant monthly value, and then smoothing the resulting series using the linear filter described by Slade (1995) and used by

Besanko, Gupta and Jain (1998) for a similar purpose: $v_{kt} = 0.25\,\hat{v}_{k,t-1} + 0.50\,\hat{v}_{k,t} + 0.25\,\hat{v}_{k,t+1}$. Table 1 summarizes all of the price and quantity data use in the estimation procedure.

[table 1 in here]

Results and Implications

In this section, we present the results obtained from estimating both stages of the strategic price-promotion model and draw several implications for industry practice and the apparent conduct of industry members. Recall that the empirical model describes an equilibrium in mixed strategies. Therefore, the first set of results describe the probability that a retailer offers a sale during a particular week. These results are reported in table 2. Given that the R^2 value is 54.8% and all coefficients are significant and of the expected sign, we believe the probit model provides an acceptable fit to the data. Among the individual parameter estimates, we find that the average probability that a product will go on sale in a given week is 25.9%, or roughly once every four weeks.[5] This result is consistent with information provided by industry officials. Second, all seven included products are less likely to be put on sale relative to bananas. Third, chain 1 promotes more frequently than the excluded chain (chain 4), while chain 3 promotes less frequently. Fourth, fresh produce sales are less likely during summer and fall when the demand for fresh fruit tends to be relatively high – a result that appears to contradict the findings of Warner and Barsky (1995) and MacDonald (2000) who report lower prices during periods of peak demand. This result may be due to the fact that we also control for the absolute level of

[5] It is important to note that the parameters reported in table 2 are interpreted as the marginal effects of each explanatory variable on the probability of observing a sale in a given week. They are calculated by multiplying the marginal utility parameters, γ, by the associated density function value: $f(\hat{\gamma}'z)$. In table 2, we also report the probability-elasticity with respect to each explanatory variable in order to provide a clearer interpretation of each effect.

retail and wholesale prices in this model. Prices may indeed be lower during these periods, but not promoted as frequently. Wholesale prices have the expected effect on the probability of a sale as higher prices during the previous week reduce the probability that an item is offered on sale in the current week. Similarly, the probability of an item being discounted in the current week also falls in the number of products promoted during the previous week. Given that all chains in the L.A. market are characterized as HI-LO, this finding is to be expected. Finally, the probability of a sale rises in lagged retail prices as predicted by the intertemporal-demand models of Pesendorfer (2002) or Hosken and Reiffen (2001). Relatively high prices for products that can be stored for more than one week (apples, oranges and grapes in our data) lead to an accumulation of demand among "cherry pickers" or those who wait for sales to buy certain products.

[table 2 in here]

Next, we present the results of the second-stage demand, price and sale product response model. These results are shown in table 3. There are, in general, two widely accepted measures of goodness-of-fit for a NL3SLS model: (1) a system-wide coefficient of determination (R^2) and (2) the quasi-likelihood ratio (QLR) test of Gallant and Jorgenson (1979). Prior to interpreting these measures, however, we first regress retail prices on the set of instruments in order to assess the appropriateness of the instrumental variables estimator. This regression provides an R^2 value of 0.944 (not shown in the table), so the instruments used to generate these results are highly correlated with the included endogenous variables. Using these instruments, the system R^2 value is 0.865, which is relatively high given the parsimony of the model and paucity of time-series observations in the scanner data. Further, in applying the QLR test we easily reject the null hypothesis that all system parameters are equal to zero so we are confident that the model provides an acceptable fit to the data.

[table 3 in here]

With a nested logit model, the critical parameters consist of the within-store and across-store substitution parameters, σ_I and σ_J, respectively. According to Slade (1995), we should expect the elasticity of substitution among products within a store to be greater than among stores because consumers are more likely to compare different brands or varieties of the same product within a store than compare prices of products between stores. However, Anderson and DePalma (1992) describe an opposite possibility. Namely, if consumers purchase different products in the same store intending to meet distinctly different needs, then we would expect the elasticity of substitution among stores to be greater than among products within a store. While Slade's (1995) logic may apply to a brand-level analysis, the same is not likely to be true at the category- level. In fact, we find that the elasticity of substitution among stores is significantly greater than within each particular store (0.988 > 0.788). This result suggests a number of important implications for the conduct of retailer promotion strategy. First, if consumers regard their entire shopping basket as highly substitutable among stores, then a chain's share of the total retail grocery market is a critical determinant of how much it can mark products up over wholesale cost. Second, while inter-brand cannibalization is likely to occur as a result of promoting an individual product, inter-category substitution is not. Therefore, adopting a category-focus to promotion strategy is likely to be effective. Third, many authors have used evidence of consumer in-store shopping behavior to support their assumption that supermarket retailers operate as local monopolists and, thereby, do not behave strategically (Slade, 1995;

Besanko, Gupta and Jain, 1998, for example). However, if our results are indeed true, then ignoring interaction among chains represents a significant conceptual and empirical misspecifcation.

Explicitly estimating inter-chain interaction parameters is one way of addressing this concern. To test the "retail monopoly" hypothesis, we first use the results in table 3 to test whether all of the price-reaction parameters are jointly equal to zero, then whether all of the sale-product-number parameters are equal to zero, and finally whether all price and sale product response parameters are equal to zero. With four degrees of freedom at a 5% level of significance, we easily reject the first null hypothesis that all of the price-response parameters are equal to zero as the Wald chi-square test statistic is 7,542.7 while the critical value is 9.49. Similarly, we reject the null that all sale-product response parameters are equal to zero as the Wald statistic is 127.8. In the final case, there are eight restrictions so the critical chi-square statistic of 15.5 is still far below the test value of 7,924.5. Therefore, we can conclude that supermarket retailers in the same geographic market take into account both their rivals' prices and the number of products their rivals have on promotion each week when deciding their own promotion strategy.

By estimating a structural game-theoretical model of retailer conduct, we can also compare observed outcomes to standards of competitive behavior (Gasmi, Laffont and Vuong, 1992; Genesove and Mullin, 1998; Kadiyalia, Vilcassim and Chintagunta, 1999; Sudhir, 2001, and many others). Namely, if the estimated response parameters are equal to zero, then retailers behave as Bertrand oligopolists and prices should approximate perfect competition. Similarly, if the sale-product response parameters are also equal to zero, then rivals clearly do not compete in either the breadth or depth of price promotions. On the other hand, positive response parameters suggest some degree of tacitly collusive pricing behavior. These parameters are more conveniently interpreted as response elasticities (Baker and Bresnahan, 1985), which we present in table 4. In terms of response elasticities, a value of zero indicates perfectly competitive behavior, while an elasticity greater than zero suggests that retailers price cooperatively. With respect to price-responses, the upper panel in table 4 shows that retailer price behavior is neither perfectly competitive nor completely collusive. Retailers 1 and 3 appear to respond most weakly to rival price changes, while retailer 4 is particularly aggressive in responding to price changes by chain 1. From equation (24) above, it is clear that retail margins rise in the elasticity of price response, holding cross-price elasticities constant. Said differently, as retailers move toward more cooperative pricing strategies, the margin for each individual product rises. In terms of the number of sale products, all response elasticities are again positive, but significantly smaller in magnitude than the price-response elasticities. For example, if retailer 2 increases the number of products he has on sale by 10.0%, then retailer 1 will respond by adding another 3.7% of its own products on sale. Among all chains, retailer 1 appears to be the most accommodative with respect to the number of sale products, while it was among the least cooperative in pricing. Finding uniformly cooperative promotional behavior among our sample retailers is perhaps not surprising given the elasticity of substitution results reported above. Increasing market share by either increasing the depth or breadth of promotions can be expected to elicit a similar response among rivals, so the cost of doing so can be substantial. Whether the overall gain warrants an aggressive strategy, however, depends on the promotion elasticity at each level.

[table 4 in here]

"Partial" demand elasticities, or elasticities estimated without accounting for rival responses, provide only part of the answer. Table 5 provides estimates of the partial demand elasticities, or measures of the gross response in demand for a retailer's own product with respect to a change in its price. From this table, it is evident that demands are highly elastic, as to be expected from item-level data. Further, all other products in the same store, and those at all other stores, are weak substitutes. Unlike other store-level nested logit demand models, however, the relatively high elasticity of substitution among stores means that the cross-price elasticities for products in the same store are not necessarily an order of magnitude greater than for products in other stores (Dhar and Cotterill, 2003). Finding relatively high cross-price elasticities of demand between products in different stores also provides some evidence contrary to the assumption that supermarkets exist as local monopolies.

[table 5 in here]

Marketing managers, however, are likely to be more interested in residual demand elasticities disaggregated into the four components described above: product demand conditional on store choice, store choice conditional on category choice, unconditional category choice, and reaction to rival's expected price changes. Table 6 shows each of these elasticities for a representative chain. Whereas the elasticities in table 5 do not allow for rival price response, the estimates in table 6 take equilibrium price responses into account. Uniformly, discounting has its greatest impact on a product's share within the promoting store. The reason is clear by inspecting equation (27). While greater store-heterogeneity reduces the impact of a price-promotion on store-share, this same effect is attenuated at the individual product-level by product-heterogeneity. Intuitively, promotion will always have a greater impact on product-share than store-share because products can draw consumers from two places: other products within the store and other stores, whereas new store traffic can only come from other stores, or from other product categories. Notice, however, that promotion effectiveness may fall in both product- and store-heterogeneity, but margins in (23) are higher in each case. This represents the fundamental tradeoff in determining promotion efficiency – accepting lower margins for a greater ability to increase volume through short-term price reductions. Decomposing promotion elasticities in this way also shows that very little of the increase in volume comes from other product categories, or the outside option. This is consistent with other studies that find only a small portion of the effect of any price change comes from higher purchase quantities, while most of the impact comes from brand switching and purchase acceleration (Neslin, Henderson, and Quelch, 1985; Gupta, 1988; Nijs, et al., 2001; Pauwels, et al., 2002). Particularly in the case of perishable food products, consumers are unlikely to change their aggregate budget allocations in response to a deal on a relatively small item.

Rival reactions to a price discount, on the other hand, impact promotion effectiveness in a much more significant way, reducing the impact of a sale by over 10% in most cases. The magnitude of this effect depends, in turn, on three parameters: rivals' price-response elasticity and the degree of store- and product-heterogeneity. Clearly, the more aggressive rival chains are in matching price discounts, the less effective they will be in building market share for the promoting store. These reactions, however, can be mitigated to a certain extent by better differentiating both the promoting store and the products that are put on sale. Managing product-level decisions such as assortment, vertical differentiation or private-label strategies can reduce the extent to which consumers substitute among stores, thereby reducing rivals' power to counter a price-promotion. Consequently, the tradeoff between more effective promotions and lower margins cited above is significantly more complicated when rival reactions are taken into account. Strategic promotion decisions, therefore, are more likely to involve product differentiation, sacrificing the ability to gain share through discounting, but earning higher margins and protecting any sale strategy from rival reactions.

[table 6 in here]

Conclusions and Implications

This study provides a new way of looking at the effectiveness of retail price promotions among perishable grocery products. By allowing for differing degrees of heterogeneity among products and among stores, we are able to determine where price promotion is likely to have its greatest effect – whether at the store-level or at the product-level. A conceptual model of retail promotions based on a nested-logit structure shows that price promotion is likely to have its greatest impact on product-share within a particular chain if products are highly substitutable, but stores are not. On the other hand, promotions are likely to increase store share if consumers regard chains as highly substitutable.

An empirical application of the nested logit model that allows for strategic responses in both prices and the number of products offered on sale helps to resolve this fundamentally empirical question. We estimate a structural model of retail equilibrium in two stages. In the first stage, we estimate a probit model of the probability that an individual product is offered on sale during a particular week Given that the sale-decision is endogenous, we substitute fitted values for probability of a sale into the second-stage equilibrium model. We apply this empirical procedure to two years of weekly scanner data for eight perishable products in the fresh fruit category for four major chains in the Los Angeles market.

We find that price-promotion does indeed increase demand and cause it to become less elastic, both desirable outcomes from a retailer's perspective. Retail sales also increase in the number of products offered on sale each period, suggesting that consumers derive utility not just from the depth of a promotion, but from its breadth as well. Promotion effectiveness, however, measured as the residual demand elasticity for each product, depends critically on the elasticity of substitution among products (the first nest) and among stores (the second, or upper nest), and the extent two which rivals respond with promotions of their own. With respect to the degree of heterogeneity among stores and products, we find that the elasticity of substitution among stores is greater than the elasticity of substitution among products within each store. We interpret this result as evidence that different products within the same store fulfill fundamentally different consumer needs. Further, the estimated price-response parameters are significantly greater than zero, or less competitive than Bertrand-Nash. While this result is typically interpreted as evidence in support of some sort of tacit collusion, in this case it means that rivals are more likely to match any price reduction than if discounts were purely exogenous. This also means that the residual demand elasticity is reduced by the extent of the price reaction. Decomposing the residual demand elasticity, however, into product, store, category and rival response components shows that promotions have their greatest impact at the product level, followed by the competitive response by rivals and, finally, by building store share. Any category impacts are minimal at best.

The results reported here contain a number of important implications for promotion strategy. First, retail managers must be conscious not only of how deep they cut prices, but also the number of products in the same category that are offered on sale at one time. Second, short-term price discounts can increase demand both directly by inducing substitution away from other products, and indirectly by accelerating purchases or causing consumers to stockpile. The direct effect will be stronger, however, the less differentiated are both the promoted products, and the stores doing the promotion. Third, reactions by rivals can significantly reduce the effectiveness of a given promotion, so promotions are perhaps best targeted toward brands or varieties unique to the promoting store. While fresh fruit provides a unique context with which to test hypotheses regarding retail sales, the findings reported here are likely to extend to consumer packaged goods of all types. In particular, the trend toward store brands represents one way in which retailers are responding to the fundamental economics underlying price promotion. By promoting a highly substitutable national brand, retailers can then increase profits by offering new customers a higher-margin alternative and, at the same time, limiting competitive responses to their higher-profit items. Future research in this area would benefit by answering the types of questions posed here in a variety of different products, from a packaged perishable product such as yogurt, to a more storable item such as ketchup or coffee.

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Table 1. Summary Description of Data

Variable	N	Mean	Std. Dev.	Minimum	Maximum
Store Volume (m lbs./wk.)	104	13.312	0.095	13.149	13.477
Outside Share	3328	0.265	0.061	0.034	0.399
Marginal Product Share	3328	0.023	0.034	0	0.284
Conditional Product Share	3328	0.125	0.168	0.000	0.806
Store Share 1	104	0.107	0.021	0.059	0.152
Store Share 2	104	0.209	0.032	0.147	0.296
Store Share 3	104	0.202	0.019	0.170	0.259
Store Share 4	104	0.218	0.033	0.153	0.388
Retail Price ($/lb.)	3328	2.428	1.941	0.000	14.471
Probability of Discount	3328	0.170	0.376	0.000	1.000
Number of Sale Products	3328	4.077	3.119	0.000	17.000
Number of Total Products	3328	61.786	8.471	39.000	77.000
Wholesale Price ($/lb.)	104	0.702	0.860	0.088	3.383
Input Price 1	104	3.215	0.081	3.011	3.409
Input Price 2	104	4.341	0.141	4.063	4.668
Input Price 3	104	6.614	0.222	6.075	7.025
Input Price 4	104	1.552	0.030	1.465	1.648
Input Price 5	104	3.123	0.052	2.953	3.226
Input Price 6	104	3.639	0.044	3.553	3.729
Input Price 7	104	1.345	0.022	1.309	1.386
Input Price 8	104	0.092	0.002	0.090	0.096

Table 2. Probit Model of Price Promotions: L.A. Supermarket Chains

Variable	Estimate	t-ratio	Elasticity
Constant[a]	0.259	1.996	0.399
Product 1	-0.568	-5.874	-0.070
Product 2	-1.078	-9.917	-0.168
Product 3	-0.421	-3.974	-0.043
Product 4	-0.481	-4.393	-0.055
Product 5	-0.522	-5.514	-0.062
Product 6	-0.772	-7.663	-0.111
Product 7	-0.809	-6.197	-0.154
Chain 1	0.178	2.454	0.076
Chain 2	0.071	0.944	0.033
Chain 3	-0.153	-1.952	-0.055
Spring	0.031	0.425	0.014
Summer	-0.291	-3.693	-0.111
Fall	-0.187	-2.522	-0.067
r_{t-1}	-0.119	-4.654	-0.05
p_{t-1}	0.095	3.565	0.298
n_{t-1}	-0.009	-3.22	-0.049
R^2 **(McFadden)**	0.548		
LLF	-1435.912		

[a] In this table, r_{t-1} is the wholesale price of product i in the previous week, p_{t-1} is the lagged retail price, and n_{t-1} is the lagged number of sale products. A single asterisk indicates significance at a 5% level. Elasticity estimates are calculated at sample means and represent the percentage change in the probability of a sale for a percentage change in the value of each explanatory variable. The R^2 measure is calculated using the definition of McFadden (1974), or $R^2 = 1 - LLF(\hat{\gamma})/LLF(\mathbf{0})$, where $LLF(\,)$ represents the log-likelihood function evaluated at the estimated parameters and a null model, respectively.

Table 3. Structural Nested Logit Model of Sales Behavior: L.A. Supermarket Chains

Demand Equation			Price Response			Number of Sale Products		
Variable	**Estimate**	**t-ratio**	**Variable**	**Estimate**	**t-ratio**	**Variable**	**Estimate**	**t-ratio**
Chain 1[a]	-2.679*	-8.904	**Chain 1**	0.661	0.348	**Chain 1**	-3.151*	12.443
Chain 2	-2.767*	-7.742	**Chain 2**	0.824	0.434	**Chain 2**	-3.676*	14.517
Chain 3	-2.195*	-6.166	**Chain 3**	1.285	0.677	**Chain 3**	-4.154*	16.406
Chain 4	-2.629*	-7.635	**Chain 4**	1.155	0.608	**Chain 4**	-4.027*	15.904
Product 1	1.344*	6.892	**Product 1**	-2.282*	-38.884	**Product 1**	-1.618*	-6.985
Product 2	-1.039*	-5.222	**Product 2**	-2.195*	-36.381	**Product 2**	-0.195	-0.976
Product 3	0.503*	3.219	**Product 3**	-1.204*	-20.151	**Product 3**	-0.497*	-2.500
Product 4	0.151	1.004	**Product 4**	-0.980*	-16.743	**Product 4**	-0.390	-1.945
Product 5	-0.337	-1.723	**Product 5**	-2.362*	-39.968	**Product 5**	-0.371	-1.809
Product 6	-0.880*	-4.811	**Product 6**	-2.028*	-33.546	**Product 6**	-0.335	-1.688
Product 7	3.906*	26.579	**Product 7**	0.464*	7.543	**Product 7**	-4.120*	-11.830
$\boldsymbol{d}_{ij}$	6.166*	9.830	$\boldsymbol{v}_1$	0.009*	3.591	$\boldsymbol{v}_5$	0.008	0.472
$\boldsymbol{d}_{ij}\boldsymbol{p}_{ij}$	-0.836*	-4.569	$\boldsymbol{v}_2$	-0.007	-1.723	$\boldsymbol{v}_6$	-0.104*	-2.915
$\boldsymbol{n}_j$	1.075*	19.072	$\boldsymbol{v}_3$	-0.032*	-2.010	$\boldsymbol{v}_7$	0.008	0.609
$\boldsymbol{m}_j$	0.152*	3.329	$\boldsymbol{v}_4$	0.486*	3.595	$\boldsymbol{v}_8$	3.498*	8.344
α	0.327*	11.87	ϕ_1	1.659*	41.453	ψ	19.917	1.008
σ_I	0.789*	68.214	ϕ_2	1.526*	46.86	γ_1	0.105*	3.153
σ_J	0.988*	359.100	ϕ_3	1.356*	71.251	γ_2	0.349*	6.598
			ϕ_4	1.165*	39.226	γ_3	0.207*	6.054
						γ_4	0.490*	7.726
R^2	0.865							
χ^2	102.282							

[a] In this table, $\hat{d}_{ij}$ is the predicted probability of a sale calculated from the first-stage probit equation, $\hat{d}_{ij}p_{ij}$ is an interaction term between the predicted sale probability and retail price, n_j is the number of sale products offered by chain j in week t (t subscript is suppressed), m_j is the total number of products offered by chain j, α is the price-coefficient, σ_I is the elasticity of substitution among products, and σ_J is the elasticity of substitution among stores. For all estimates, a single asterisk indicates significance at a 5% level. The χ^2 statistic is the quasi-likelihood ratio test of Gallant and Jorgenson (1979) that compares the minimized NL3SLS objective function value (Q_1) with a null model (Q_0): $\chi^2 = (Q_0 - Q_1)$. The test statistic has q degrees of freedom, where q is the number of parameters that are restricted to equal zero in the null model (54). The critical value for this test at a 5% level is 72.153.

Table 4. Price and Sale Product Response Elasticities: L.A. Supermarket Chains

	Response of:			
With Respect to:[a]	p_1	p_2	p_3	p_4
p_1	1	0.359*	0.881*	3.184*
	N.A.	-46.86	-7.125	-39.226
p_2	0.754*	1	0.400*	1.447*
	-41.453	N.A.	-7.125	-39.226
p_3	0.670*	1.355*	1	1.285*
	-41.453	-46.86	N.A.	-39.226
p_4	0.607*	1.229*	0.323*	1
	-41.453	-46.86	-7.125	N.A.

	Response of:			
With Respect to:	n_1	n_2	n_3	n_4
n_1	1	0.140*	0.241*	0.210*
	N.A.	3.152)	-6.598	-6.054
n_2	0.367*	1	0.180*	0.157*
	-7.726	N.A.	-6.598	-6.054
n_3	0.710*	0.203*	1	0.304*
	-7.726	3.152)	N.A.	-6.054
n_4	0.484*	0.138*	0.238*	1
	-7.726	3.152)	-6.598	N.A.

[a] Table entries are interpreted as the average response elasticity of prices in chain *i* with respect to a change in the price of a product in chain *j* and the average response elasticity of sale product numbers in chain *i* with respect to a change in the number of sale products offered in chain *j* in the upper and lower panels, respectively. For all elasticity estimates, a single asterisk indicates significance at a 5% level.

Table 5. Nested Logit Partial Price Elasticities: L.A. Supermarkets, Chain 1

With Respect to:[a]		Percentage Change in: s_{11}	s_{12}	s_{13}	s_{14}	s_{15}	s_{16}	s_{17}	s_{18}
Chain 1	p_1	-11.82	0.098	0.141	0.070	0.084	0.056	0.466	0.009
	p_2	0.222	-11.542	0.119	0.058	0.074	0.050	0.401	0.008
	p_3	0.412	0.157	-20.671	0.104	0.138	0.092	0.739	0.014
	p_4	0.524	0.193	0.235	-26.867	0.173	0.125	0.916	0.017
	p_5	0.221	0.089	0.155	0.074	-12.511	0.038	0.425	0.008
	p_6	0.307	0.122	0.199	0.096	0.098	-17.388	0.580	0.011
	p_7	1.266	0.484	0.712	0.340	0.420	0.272	-48.224	0.043
	p_8	0.673	0.246	0.341	0.162	0.236	0.147	1.228	-36.994
Chain 2	p_1	0.193	0.076	0.109	0.056	0.064	0.042	0.36	0.007
	p_2	0.197	0.077	0.115	0.057	0.066	0.043	0.365	0.007
	p_3	0.434	0.165	0.229	0.109	0.144	0.098	0.787	0.015
	p_4	0.508	0.193	0.252	0.121	0.168	0.118	0.910	0.017
	p_5	0.163	0.064	0.105	0.050	0.052	0.032	0.302	0.006
	p_6	0.245	0.100	0.18	0.084	0.075	0.042	0.484	0.009
	p_7	1.286	0.493	0.72	0.347	0.429	0.278	2.327	0.044
	p_8	1.122	0.424	0.629	0.296	0.372	0.239	1.984	0.038
Chain 3	p_1	0.245	0.094	0.136	0.066	0.080	0.053	0.448	0.008
	p_2	0.278	0.106	0.154	0.072	0.089	0.063	0.504	0.009
	p_3	0.526	0.200	0.263	0.124	0.173	0.118	0.936	0.018
	p_4	0.538	0.204	0.266	0.126	0.179	0.121	0.952	0.018
	p_5	0.237	0.091	0.13	0.064	0.077	0.049	0.431	0.008
	p_6	0.299	0.119	0.21	0.099	0.098	0.050	0.571	0.011
	p_7	1.207	0.462	0.673	0.323	0.399	0.256	2.179	0.041
	p_8	1.634	0.622	0.891	0.431	0.545	0.355	2.946	0.056
Chain 4	p_1	0.231	0.089	0.132	0.064	0.077	0.049	0.419	0.008
	p_2	0.305	0.117	0.177	0.085	0.101	0.065	0.553	0.011
	p_3	0.487	0.181	0.241	0.114	0.163	0.109	0.836	0.016
	p_4	0.523	0.192	0.256	0.116	0.179	0.115	0.887	0.017
	p_5	0.256	0.100	0.152	0.075	0.083	0.052	0.472	0.009
	p_6	0.294	0.116	0.200	0.096	0.094	0.053	0.549	0.011
	p_7	1.377	0.528	0.79	0.378	0.455	0.291	2.488	0.047
	p_8	1.276	0.488	0.736	0.351	0.421	0.268	2.296	0.044

[a] Each entry in this table represents the percentage change in the share of product i in chain 1 (s_{1i}) with respect to a percentage change in the price of each product / chain pair. The elasticity estimates for all other chains show a similar pattern, but are not shown here due to space limitations. They are available from the contact author.

Table 6. Nested Logit Residual Demand Elasticities: L.A. Supermarkets

Chain	Product	$\theta^R_{i,j}$	$\theta_{i\mid j}$	$\theta_{j\mid J}$	θ_J	$\sum_{-i}\sum_{-j}\theta_{i,j}$
1	1	-11.118	-11.884	-0.497	-0.031	1.263
1	2	-10.502	-11.567	-0.198	-0.01	1.263
1	3	-19.929	-20.752	-0.439	-0.025	1.263
1	4	-25.970	-26.997	-0.235	-0.012	1.263
1	5	-11.402	-12.502	-0.162	-0.008	1.263
1	6	-16.183	-17.321	-0.125	-0.006	1.263
1	7	-51.403	-49.213	-3.450	-0.269	1.263
1	8	-35.529	-36.737	-0.055	-0.003	1.263
2	1	-6.918	-9.396	-0.353	-0.040	2.832
2	2	-8.112	-10.826	-0.117	-0.011	2.832
2	3	-20.447	-22.996	-0.282	-0.030	2.832
2	4	-24.107	-26.649	-0.290	-0.031	2.832
2	5	-6.258	-8.990	-0.099	-0.010	2.832
2	6	-11.549	-14.246	-0.135	-0.014	2.832
2	7	-45.760	-44.856	-3.730	-0.665	2.832
2	8	-59.405	-62.158	-0.079	-0.007	2.832
3	1	-9.820	-11.788	-0.437	-0.048	2.405
3	2	-13.007	-15.377	-0.035	-0.003	2.405
3	3	-25.713	-27.914	-0.204	-0.020	2.405
3	4	-26.587	-28.817	-0.175	-0.017	2.405
3	5	-10.397	-12.645	-0.157	-0.015	2.405
3	6	-15.022	-17.337	-0.090	-0.008	2.405
3	7	-35.254	-34.339	-3.312	-0.798	2.405
3	8	-88.584	-90.869	-0.120	-0.011	2.405
4	1	-8.550	-10.702	-0.477	-0.060	2.629
4	2	-14.574	-17.186	-0.017	-0.002	2.629
4	3	-22.690	-24.986	-0.333	-0.035	2.629
4	4	-24.530	-26.864	-0.295	-0.032	2.629
4	5	-11.821	-14.381	-0.070	-0.007	2.629
4	6	-14.114	-16.583	-0.160	-0.016	2.629
4	7	-46.220	-44.867	-3.974	-0.840	2.629
4	8	-68.708	-71.157	-0.18	-0.017	2.629

[a] The values of $\theta^R_{i,j}$ represent residual demand elasticities for product *i* sold by retailer *j*. All elasticities are statistically significant at a 5% level.