A Nested Logit Model of Strategic Promotion

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Abstract:

There are many reasons why retailers use temporary price promotions, or sales, but little empirical research on their strategic role. In this paper, we estimate a discrete choice model of promotion rivalry in order to test competing hypotheses regarding the nature of the price-promotion game played among supermarket retailers. The model also differentiates between intra-store and inter-store sale effects. The results show that retailers in the same market set prices and promotion strategies in a moderately cooperative way. Further, promotion has a greater impact on product share within a store than a store's market share, because the elasticity of substitution among products is larger than the elasticity of substitution among stores. Consequently, promotion has its greatest value in driving demand for differentiated products in markets with heterogeneous retailers, perhaps explaining the trend toward premium private label products.

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

JEL Codes: L13, L66, L81, M31, C35.

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1. Introduction

Despite the ubiquitous nature of retail price promotions – sales – there is little common ground 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 others interested in the competitiveness of the retail sector. In fact, the wave of mergers among U.S. grocery retailers in the late 1990s led to widespread concern that greater concentration would lead to higher prices for food and all manner of staple goods (Hosken and Simpson, 2001). While most models of retail pricing behavior rest on the assumption that firms operate in either competitive or monopolistically competitive markets (Bliss, 1988), retail grocery markets are highly concentrated at the local level, leading to either spatial monopoly (Slade, 1995) or at least oligopoly behavior. If it is the latter, then we would expect to see price promotions being used strategically rather than as tools of price discrimination or loss-leadership. The objective of this paper is to examine whether this is indeed the case using a highly detailed, product-level retail data set.

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 that consist of either 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 purchased infrequently 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), and Hosken and Reiffen (2001) explicitly allow for multiple-product interactions in which loss-leadership emerges as the dominant rationale for price promotions. These 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. Lal and Matutes (1994), on the other hand, develop a model of loss-leadership in imperfect competition (duopoly) in which the equilibrium is unique, but it is not clear how this model generalizes to an environment of multiple firms selling many products nor how its predictions may be tested in real-world data. McAfee (1995) constructs a theoretical model of competitive equilibrium price dispersion in which the multi-product outcome is fundamentally different from the single-product mixed-strategy equilibrium of Varian (1980) or Burdett and Judd (1993) and that, in fact, an equilibrium price dispersion is not necessarily unique. Most importantly, McAfee (1995) argues that when a consumer buys many goods from multiple stores, it does not necessarily follow that all goods are bought from the store that offers the lowest total expenditure. Rather, consumers buy each good from the store that offers it at the lowest price – the fact that retailers sell multiple goods means that these minimum prices depend on the prices offered on all other goods. Although this model predicts a loss-leader-like result, it does not generate any truly interesting, testable hypotheses. However, McAfee's (1995) model does suggest that the multi-product case must take into account the probability that each product is offered for sale in a given week, rather than just the magnitude of the available discount as in Chintagunta (2002)

Because price promotion now dominates most suppliers' marketing budgets, it is somewhat surprising that there is little empirical 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. Villas-Boas (1995) adopts a different approach by directly estimating the parameters of the price distribution implied by Varian's (1980) model of equilibrium price dispersion. Because he finds some evidence that observed coffee and saltine prices could indeed have been drawn from the expected density, he interprets the result as supporting the existence of a mixed strategy equilibrium in the prices of these two products. As with many of the theoretical models cited above, however, without considering multiple products sold by many competitors the relevance of this empirical result is not clear. Moreover, as Pesendorfer (2002) points out, the random price behavior that emerges from a mixed strategy equilibrium is fundamentally inconsistent with observed retail prices that tend to stay fixed for long periods of time and then fall briefly, returning to their previous levels within a week or two. Based on the empirical evidence, therefore, the true motivation for offering price promotions in a multi-product retail environment remains to be settled.

For promotion to be effective from a retailer's perspective, discounting prices must increase store traffic and not simply reallocate demand from loyal customers 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 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. Consequently, the objective of this study is to determine whether supermarket retailers in a specific geographic market use price promotions in order to gain market share from their rivals. By testing the strategic motivation for price promotions, the study also represents a test of Varian's (1980) hypothesis that sales are a mixed strategy equilibrium. If sales are indeed the outcome of a mixed strategy equilibrium among competing retailers, then we would expect to see completely random prices. On the other hand, if it is possible to identify price patterns consistent with a pure strategy Nash equilibrium among retailers, then we can reject the Varian (1980) model.

Our findings are as follows. First, in the context of a nested logit model of retail pricing, we show that price promotions are likely to have their greatest impact on store-revenue if the degree of heterogeneity among stores is low, but heterogeneity among products is high. Said differently, sales will be effective if stores are highly substitutable, but products are not. Second, an empirical application of this model finds that price promotions are indeed effective in both increasing the unconditional (marginal) market share of the promoted product and reducing its demand elasticity as well. Third, we find that the elasticity of substitution among supermarkets in the L.A. metro area is indeed significantly lower than the elasticity of substitution within each store, but not zero as many authors assume. Therefore, price-promotion is likely to build store traffic, but also cannibalizes sales from non-promoted products. Finally, by allowing for a general form of Nash interaction in both shelf prices and discounts, the empirical results show conduct that is significant less competitive than Bertrand in both cases. Consequently, despite assertions to the contrary in the academic literature, supermarket retailers do apparently price and promote their products in a strategic way.

The rest of the paper is organized as follows. The next section consists of an empirical model of consumer demand, pricing and promotion strategy based on the variance components nested logit of Cardell (1997) and Berry (1994). The third section describes the data used to estimate the model and, specifically, why fresh produce represents a better opportunity to study retailer pricing behavior than the more usual consumer packaged goods case. This section also provides more detail on the estimation method used, including a description of the instrumental variables method and our choice of instruments. 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.

2. Economic Model of Sales

2.1 Overview

As in Chintagunta (2002), retail demand depends on a household's inherent preference for a particular store and product, the product's shelf price, promotional activity and a set of factors that are unobservable to the econometrician, but known to the retailer and the consumer. On the supply side, retailers are assumed to compete in each market as price-setting, multi-product oligopolists. Pricing decisions, however, consist of three components for each product: (1) a normal, or long-term shelf price, (2) a short-term temporary promotion price, and (3) the frequency that each product is offered on promotion. Shelf prices are set in order to maximize current profit given their assessment of market demand and rival pricing behavior. Promotional strategies are based on the realization that additional profits may be earned in the short run by exploiting the fact that shopping entails significant fixed costs on the part of consumers. Consumers from rival stores may be attracted by the expectation of receiving a lower price for a particular product, but once in the store these consumers also buy a number of higher margin products. In this study, therefore, we hypothesize that the objective of offering promotional prices is to drive traffic for the entire store, thereby building market share and higher aggregate profit.

Each week, retailers choose sale prices and the number of products to put on sale in order to maximize store profit. Assuming the total number of products displayed each week is fixed, choosing the number of products to offer on promotion is equivalent to choosing the proportion to offer on sale, or the probability that each product is offered on sale in a particular week. Expressed this way, our approach offers another estimating the class of discrete game model described by Bresnahan and Reiss (1991). While they suggest a sequential approach to estimating what amounts to an endogenous dummy variable model, the method described below retains the cross-equation restrictions necessary to test for strategic interaction among many players in a simultaneous-move game. This is not possible with a sequential estimation method. Because both variables at this stage are necessarily endogenous when retailers behave strategically, prices and the proportion of products offered on promotion are assumed to be correlated with the errors in the demand equation. Following Villas-Boas (1999), Chintagunta (2002) and others, therefore, we use a simultaneous, instrumental-variables estimator for the demand, retail price and sales strategy equations. Consequently, the empirical model consists of three equations: (1) demand, (2) retail price and (3) the proportion of products offered on sale.

2.2 Demand

Retail demand for fresh produce is derived within 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}), a binary variable that assumes a value of 1.0 if product i is offered for sale in store j in a given week (d_{ij}), an interaction term between the shelf price and the sale indicator ($d_{ij}p_{ij}$) and a set of store, product and seasonal effects ($\boldsymbol{x}_{ij}$). Utility, therefore, is written as:

$$u_{ijh} = x_{ij}^{\prime}\beta - \alpha_0 p_{ij} + \alpha_1 d_{ij} + \alpha_2 d_{ij} p_{ij} + \eta_{1ij} + v_{hj} + (1-\sigma_J)v_{ih} + (1-\sigma_I)(1-\sigma_J)\epsilon_{ijh}, \quad \textbf{(1)}$$

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, advertising, or anticipated shortages. Specifying the binary promotion variable as a direct argument of the utility function, in addition to the shelf price, is consistent with previous empirical studies (Chintagunta, 2002) and reflects the fact that promotion has a "second order" or announcement effect in addition to merely reducing the price.[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.

The demand system implied by (1) 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 $(v_{ih} + (1 - \sigma_I)\epsilon_{ijh})$ 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

[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.

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 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 (1), following Berry (1994) the level of mean utility for each choice of product i and store j is: $\delta_{ij} = x_{ij}\beta - \alpha p_{ij} + \alpha_0 d_{ij} + \alpha_1 d_{ij} p_{ij} + \eta_{1ij}$. 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:

$$E_I = \sum_{i \in I} e^{\delta_{ij}/(1-\sigma_J)(1-\sigma_I)}, \tag{2}$$

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

$$s_{i|j} = \frac{e^{\delta_{ij}/(1-\sigma_I)(1-\sigma_J)}}{E_I}. \tag{3}$$

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:

$$s_{j|J} = \frac{E_I^{1-\sigma_I}}{\sum_{I \in J} E_I^{1-\sigma_I}} = \frac{E_I^{1-\sigma_I}}{D_J}, \tag{4}$$

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:

$$s_J = \frac{D_J^{1-\sigma_J}}{1 + \sum_J D_J^{1-\sigma_J}}. \tag{5}$$

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:

$$s_{ij} = (s_{i|j})(s_{j|J})(s_J) = \frac{e^{\delta_{ij}/(1-\sigma_J)(1-\sigma_I)}}{E_I^{\sigma_I} D_J^{\sigma_J}(1 + \sum_J D_J^{1-\sigma_J})}, \quad i = 1,2,...I, \quad j = 1,2,...J. \tag{6}$$

where the utility of the outside option, or no purchase, has been normalized to zero. Taking logs of both sides of (6) leads to a share equation for product *i* in store *j* that is a function of the unobservable inclusive values:

$$\ln s_{ij} = \delta_{ij}/(1-\sigma_I)(1-\sigma_J) - \sigma_I \ln(E_I) - \sigma_J(D_J) - \ln(1 + \sum_J D_J^{1-\sigma_J}), \tag{7}$$

and substitution parameters at the product and store-levels. Substituting expressions for the aggregate supermarket share in (5) and the store (or more accurately, supermarket chain) share in

(4) into equation (7) and simplifying gives the marginal share of product *i* in store *j*:

$$\ln s_{ij} - \ln s_0 - x_{ij}^{/}\beta + \alpha_0 p_{ij} - \alpha_1 d_{ij} - \alpha_2 d_{ij} p_{ij} - \sigma_J \ln(s_{j|J}) - \sigma_I (1 - \sigma_J) \ln(s_{i|j}) = \eta_{1ij}, \quad \textbf{(8)}$$

where η_{1ij} is the econometric error term described in (1) above. Equation (8), 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 shelf prices and discounts, are assumed to be endogenous. Following the description of retail supply in the next section, we describe how the parameters of (8) are estimated when the variables of interest are endogenous.

2.3 Retailer Price and Promotion Decision

In order to determine whether retailers use price promotions strategically, it is necessary to characterize the supply of each product *i* from each retailer *j* described in the demand model above, including their decisions regarding the frequency of discounts. Specifically, we estimate the supply-side of the model by estimating (9) along with first-order conditions for a Nash equilibrium in sale prices and promotions in a structural model of retail demand and supply (Sudhir, 2001; Chintagunta 2002; Villas-Boas, 2003). 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 the responsibility to set prices for entire 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. At the category level, however, a manager's decision regarding promotions is more appropriately characterized in terms of the number of products offered for sale in a given week. Particularly in fresh produce, supermarkets that follow HI-LO pricing strategies (like all of the stores in the data used here) typically have a number of items on promotion each week. We write this proportion as $n_j = \sum_i d_{ij}/m_j$ where m_j is the total number of items stocked in store j.[3] Defining a retailer's promotion decision this way is also convenient because n_j is also equal to the probability an individual product is offered on sale each week. Therefore, a marginal increase in n_j by a retailer is equivalent to an increase in the probability each product is offered on sale, or the expected value of the discrete promotion indicator from a consumer's perspective. Given this assumption, the profit equation for retailer j is written as:

$$\Pi_j = Q \sum_{i \in I} (p_{ij} - c_{ij}) s_{ij} - g(n_j), \qquad \textbf{(9)}$$

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. 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

[3] Aggregating promotion decisions in this way also represents an alternative approach to estimating discrete games (Bresnahan and Reiss, 1991). Estimating separate equations for each binary discount variable would not only be intractable for reasons of dimensionality, but would require a large-scale simultaneous probit model. Sequential methods could potentially be used to estimate such a system, but as Bresnahan and Reiss (1991) point out, consistent estimates of retailer conduct could not be recovered by imposing cross-equation parameter restrictions implied by the general Nash solution. McAfee (1995) also looks at multi-product retailer price dispersion this way – each retailer chooses a probability of sale rather than a particular product to promote each week.

prices of labor, energy and marketing services. Therefore, the marginal cost function is written as:

$$c_{ij} = r_{ij} + \sum_k \tau_k w_k + \sum_k \sum_l \tau_{kl}(w_k w_l)^{1/2}, \qquad \textbf{(10)}$$

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 advertising 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 (2005):

$$g(n_j) = \lambda_0 + \lambda_1 n_j + \lambda_2 n_j^2, \qquad \textbf{(12)}$$

so the marginal cost of promotion is a linear function of the proportion 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:

$$\frac{\partial \Pi_j}{\partial p_{ij}} = Qs_{ij} + Q\sum_k \Omega_{ik}\frac{\partial s_{kj}}{\partial p_{ij}}(p_{kj} - c_{kj}) = 0, \quad i = 1,2,\ldots m, \tag{13}$$

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, (13) 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:

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

Retailers are assumed to solve the first order conditions in (13) and (14) simultaneously. Therefore, the solution is simplified considerably by writing each in matrix notation:

$$Q\boldsymbol{s} + Q(\boldsymbol{\Omega}\nabla_p)(\boldsymbol{p} - \boldsymbol{c}) = 0, \tag{15}$$

with respect to price, and:

$$Q(\boldsymbol{\Omega}\nabla_n)(\boldsymbol{p} - \boldsymbol{c}) - \nabla_g = 0, \tag{16}$$

with respect to the number of products offered for sale where ***s*** is a vector of market shares for all *m* products, ***p*** is a vector of prices, ***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 (***p*** - ***c***) and substituting into (16) 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:

$$(\boldsymbol{p} - \boldsymbol{c}) = -(\boldsymbol{\Omega}\nabla_p)^{-1}\boldsymbol{s}, \tag{17}$$

for the retail margin, and:

$$\nabla_g = -Q(\boldsymbol{\Omega}\nabla_n)(\boldsymbol{\Omega}\nabla_p)^{-1}\boldsymbol{s}, \tag{18}$$

for the number of sale products. Before (17) and (18) 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 chains 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 respond to an aggregate of each other store’s prices and not the prices of individual products. 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 (2005), Besanko, Gupta and Jain (1998) or Nevo (2001). In the empirical application below, we test whether an assumption of Bertrand-Nash pricing is more appropriate than the continuum of possible conduct parameters assumed here.

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

$$\nabla_p^{ij} = \partial s_{i,j} / \partial p_{i,j} + \sum_{-i \in I} \sum_{-j \in J} (\partial s_{-i,-j} / \partial p_{-i,-j}) \phi_{i,j}, \tag{19}$$

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:

$$\nabla_n^{ij} = \partial s_{i,j} / \partial n_{i,j} + \sum_{i \in I} \sum_{-j \in J} (\partial s_{-i,-j} / \partial n_{-i,-j}) \pi_{i,j}, \tag{20}$$

and $\pi_{i,j} = \partial n_{-i,-j} / \partial n_{i,j}$. Applying these derivatives to the marginal share equation in (7) gives expressions for the matrix of price responses in terms of the parameters of the nested logit model:

$$\begin{aligned} \nabla_p^{i,j} = \left(\frac{\alpha_0 + \alpha_2 d_{i,j}}{(1 - \sigma_I)(1 - \sigma_J)} \right) & s_{i,j} [(1 - \sigma_I s_{i|j} - \sigma_J (1 - \sigma_I) s_{j|J} s_{i|j} - (1 - \sigma_I)(1 - \sigma_J) s_{i,j}) \\ & - \sum_{-i \in I} \sum_{-j \in J} \phi_{i,j} (- \sigma_I s_{-i|-j} - \sigma_J (1 - \sigma_I) s_{-j|J} s_{-i|-j} - (1 - \sigma_I)(1 - \sigma_J) s_{-i,-j})], \end{aligned} \tag{21}$$

for all products, i, and stores, j. Substituting (21) into (17) and adding an econometric error term, the margin for product i in store j in general Nash rivalry is:

$$p_{i,j} - c_{i,j} - \left(\frac{(1-\sigma_I)(1-\sigma_J)}{\alpha_0 + \alpha_2 d_{i,j}} \right) / [(1 - \sigma_I s_{i|j} - \sigma_J (1-\sigma_I) s_{j|J} s_{i|j} - (1-\sigma_I)(1-\sigma_J) s_{i,j}) \\ - \sum_{-i \in I} \sum_{-j \in J} \phi_{i,j} (- \sigma_I s_{-i|-j} - \sigma_J (1-\sigma_I) s_{-j|J} s_{-i|-j} - (1-\sigma_I)(1-\sigma_J) s_{-i,-j})] = \eta_{2j}, \tag{22}$$

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

$$\lambda_1 + 2\lambda_2 n_j - \left(\frac{1}{\alpha_0 + \alpha_2 d_{i,j}} \right) Q(s_{i,j} + \sum_{-i \in I} \sum_{-j \in J} \pi_{i,j} s_{-i,-j})(\alpha_1 + \alpha_2 p_{i,j}) = \eta_{3j}, \tag{23}$$

where η_{2j} and η_{3j} are both identically, independently distributed error terms.[4] 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.

2.4 Heterogeneity and Promotion Effectiveness

This section investigates the implications of Nash rivalry for the impact of price-promotion on category, chain and product sales. Specifically, we determine the linkage between heterogeneity at the store- and product-level and the effect 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

[4] Note that the solution for ∇_n makes use of the fact that $n_j = \mathrm{E}[d_{ij}]$ so the derivative of mean utility in the number of sale products is: $\partial\delta_j / \partial n_j = \partial\delta_j / \partial E(d_{ij}) = \alpha_1 + \alpha_2 p_{ij}$.

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*.[5] Using equation (22), 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:

$$\theta_{i,j} = \theta_{i|j} + \theta_{j|J} + \theta_J + \sum_{-i \in I} \sum_{-j \in J} \Phi_{i,j} \theta_{-i,-j}, \tag{24}$$

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 (8), we calculate own- and cross-price elasticities both within and among stores for all products. Expanding each component of (24), the own-price

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[5] 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 from the "announcement effect" of a promotion, and (3) a rotation of the demand curve, estimated through an interaction term between the sale indicator and price variables. All three are implicitly assumed to be endogenous in the instrumental variables estimation technique described below.

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

$$\theta_{i|j} = \left(\frac{\partial s_{i|j}}{\partial p_{i,j}}\right)\left(\frac{\bar{p}_{i,j}}{\bar{s}_{i|j}}\right) = \bar{p}_{i,j}\left(\frac{\alpha_0 + \alpha_1 \bar{d}_{i,j}}{(1-\sigma_I)(1-\sigma_J)}\right)(1-\bar{s}_{i|j}), \quad \textbf{(26)}$$

while the price elasticity of conditional store choice is:

$$\theta_{j|J} = \left(\frac{\partial s_{j|J}}{\partial p_{i,j}}\right)\left(\frac{\bar{p}_{i,j}}{\bar{s}_{j|J}}\right) = \bar{p}_{i,j}\left(\frac{\alpha_0 + \alpha_1 \bar{d}_{i,j}}{(1-\sigma_J)}\right)\bar{s}_{i|j}(1-\bar{s}_{j|J}), \quad \textbf{(27)}$$

and the price elasticity of category choice becomes:

$$\theta_J = \left(\frac{\partial s_J}{\partial p_{i,j}}\right)\left(\frac{\bar{p}_{i,j}}{\bar{s}_J}\right) = (\alpha_0 + \alpha_1 \bar{d}_{i,j})\bar{p}_{i,j}\bar{s}_{i|j}\bar{s}_{j|J}(1-\bar{s}_J), \quad \textbf{(28)}$$

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:[6]

$$\theta_{-i,-j} = \bar{p}_{-i,-j}\left(\frac{\alpha_0 + \alpha_1 \bar{d}_{i,j}}{(1-\sigma_I)(1-\sigma_J)}\right)[-\sigma_I\bar{s}_{-i|-j} - \sigma_J(1-\sigma_I)\bar{s}_{-i|-j}\bar{s}_{-j|J} - (1-\sigma_I)(1-\sigma_J)\bar{s}_{-i,-j}], \quad \textbf{(29)}$$

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.

[6] 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, one that we answer using the methods described next.

2.5 Estimation Method and Instrumental Variables

In the general Nash model defined above, market share, proportion of products offered on promotion and price are assumed to be endogenous. Villas-Boas and Winer (1999) show that demand estimates will be biased and inconsistent if such endogeneity is not properly addressed. As in Nevo (2001), Chintagunta (2002) and others, we account for the endogeneity of price promotions by estimating the entire system using an instrumental variables approach, specifically generalized method of moments (GMM) (Hansen, 1982).[7] Instruments for each equation are likely to be highly correlated with demand, price or the promotion decision, but not likely to be correlated with the equation errors. For retail demand, the set of instruments consists of all of the explanatory variables in the model that are likely to be truly exogenous: input prices, wholesale fruit prices, and lagged values of the promotion and promotion-price interaction 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 (2005) use a similar approach in constructing GMM estimators for linearized logit demand systems. Following the logic of Berry, Levinsohn and Pakes (1995) and Nevo (2001), we also include prices for all other products in all other stores for each product-store observation.

For the promotion equation, the choice of instruments is based on previous theoretical

[7] We define the GMM weighting matrix as White's (1980) consistent heteroskedastic matrix wherein the weights are variances calculated from a first-stage instrumental-variable regression.

and empirical models of promotion frequency. First, promotion activity is likely to vary by product and store, so the instruments include binary indicator variables for both products and stores. 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 likely to vary by season, so we include a set 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 dynamic nature 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). Therefore, we also include lagged retail prices to account for those consumers who are able to postpone their fruit purchases until the next promotion is offered.

3. Data Description

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 temporary reduction in price, or one that is greater than or equal to 5% from the previous week's average selling price that returns to at least the previous price in the following week. 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]

4. Results and Discussion

In this section, we present the results obtained from estimating all three equations that comprise 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 both shelf prices and promotion strategies. Therefore, the first set of results are obtained from estimating the demand, price and price-promotion response model. These results are shown in table 2. There are, in general, two widely accepted measures of goodness-of-fit for a GMM 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 2 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 may not be true at the category-level. In fact, we find that the elasticity of substitution among stores is significantly less than within each particular store (0.254 < 0.912). Although consumers do appear to substitute among fruits within a store more readily than among stores, the elasticity of substitution among stores is clearly not zero.

This result suggests a number of important implications for the conduct of retailer promotion strategy. First, although consumers appear to substitute more readily within a store than among stores, they are nonetheless more willing to shop for the lowest cost basket of goods than many believe. Therefore, if consumers regard their entire shopping basket as substitutable among stores, then a chain's share of the total retail grocery market is an important determinant of how much it can mark products up over wholesale cost. Second, inter-product cannibalization is likely to be severe due to the high elasticity of substitution among products. Consequently, adopting a category-focus to promotion strategy is critically important so total store revenues are not adversely impacted. 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 central hypothesis of this paper, namely that retailers use price-promotions in a strategic way, we first use the results in table 2 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 QLR chi-square test statistic is 518.3 while the critical value is 9.49. Similarly, we reject the null that all sale-product response parameters are equal to zero as the QLR statistic is 780.9. 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 661.6. Therefore, we can conclude that supermarket retailers in the same geographic market do indeed use temporary price discounts as strategic tools, taking into account both their rivals' prices and the number of products their rivals have on promotion each week when deciding their own promotion strategy. Whether the nature of their strategy is cooperative or competitive depends on the specific value of each response parameter estimate.

By estimating a structural game-theoretical model of retailer conduct, we are able to 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 3. 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 3 shows that retailer price behavior is neither perfectly competitive nor completely collusive. Retailer 1 appears to respond most weakly to rival price changes, while retailer 3 is particularly cooperative in its response to price changes by chain 1. Although the magnitude of the estimated response elasticities is somewhat surprising, they nonetheless validate the survey results of McLaughlin, et al. (1999) who report that produce managers do indeed tend to set prices based on their perception of competitor pricing strategies. Further, 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 proportion 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 percentage of products he has on sale by 10.0%, then retailer 1 will respond by increasing the proportion of its own products on sale by 5.8%. In contrast to the price-response elasticities, 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 that the elasticity of substitution among stores is significantly greater than zero. 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 3 in here]

"Partial" demand elasticities, or elasticities estimated without accounting for rival responses, provide only part of the answer. Table 4 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 are relatively strong substitutes, while those in other stores are significantly weaker. Again, this is a reflection of the fact that, although the elasticity of substitution among stores is not zero, it is much lower than the equivalent measure among products within each store. 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). In fact, the cross-price elasticity with respect to bananas (a notorious builder of traffic for produce managers) is greater than one in all other stores. Finding relatively high cross-price elasticities of demand between products in different stores provides further evidence contrary to the assumption that supermarkets exist as local monopolies (Slade, 1995).

[table 4 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 5 shows each of these elasticities for all chain-product pairs. Whereas the elasticities in table 4 do not allow for rival price response, the estimates in table 5 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 (26). 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 (22) 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 5 in here]

5. 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 (promotion depth) and the proportion of products offered on sale (promotion breadth) is used to test which effect dominates. We estimate a structural model of retail equilibrium that includes equations for product demand, supply and promotion strategy. Given that prices, market shares and promotion strategies are jointly endogenous, we estimate the entire model using an instrumental variables procedure (GMM) in which the set of instruments is chosen in order to best explain both shelf price behavior and the incentive to offer promotions. 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.

The results show that price-promotion does indeed increase demand and cause it to become less elastic, both desirable outcomes from a retailer's perspective. This result suggests 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 products within stores is greater than the elasticity of substitution among stores. However, contrary to the maintained hypothesis in many studies in retailing, the latter is significantly different from zero. This result is interpreted as evidence that consumers do indeed substitute easily among different types of fruit based on price, but they also regard grocery stores as at least weak substitutes for each other. 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 proportion 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 from within the same store, and indirectly by drawing customers away from other stores in the same market. 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.

6. Reference List

Anderson, S. P. and de Palma, A.,1992, "Multiproduct Firms: A Nested Logit Approach." *Journal of Industrial Economics* 40: 261-275.

Baker, J. B. and T. F. Bresnahan, 1985, "The Gains from Merger or Collusion in Product-Differentiated Industries." *Journal of Industrial Economics* 33: 427-444.

Berry, S. T., 1994, "Estimating Discrete Choice Models of Product Differentiation." RAND Journal of Economics 25: 242-262.

Besanko, D., S. Gupta and D. Jain, 1998, "Logit Demand Estimation Under Competitive Pricing Behavior: An Equilibrium Framework." *Management Science* 44: 1533-1547.

Blinder, A., E. Canetti, D. Lebow, and J. Rudd, 1998, *Asking About Prices: A New Approach to Understanding Price Stickiness* New York, NY: Russell Sage Foundation.

Bliss, C., 1988, "A Theory of Retail Pricing." *Journal of Industrial Economics* 36: 375-390.

Bresnahan, T. F. and P. C. Reiss, 1991, "Empirical Models of Discrete Games." *Journal of Econometrics* 48: 57-81.

Cardell, N. S., 1997, "Variance Components Structures for the Extreme Value and Logistic Distributions with Applications to Models of Heterogeneity." *Econometric Theory* 13: 185-213.

Chevalier, J., A. Kashyap, and P. Rossi, 2000, "Why Don't Prices Rise During Periods of Peak Demand? Evidence from Scanner Data." NBER Working Paper 7981. Cambridge, MA. October.

Chintagunta, P. K., 2002, "Investigating Category Pricing Behavior at a Retail Chain." *Journal of Marketing Research* 39: 141-154.

Currie, G. R. and S. Park., 2002, "The Effects of Advertising and Consumption Experience on the Demand for Antidepressant Drugs." Working paper. Department of Economics, University of Calgary, Calgary, Alberta, Canada. March.

Dhar, T. and R. W. Cotterill, 2003, "Oligopoly Pricing with Differentiated Products: The Boston Fluid Milk Market Channel," paper presented at AAEA annual meeting, Montreal, Canada. August.

Draganska, M. and D. Jain, 2005, "Product-Line Length as a Competitive Tool." *Journal of Economics and Management Strategy* 14: 1-28.

Epstein, G. S., 1998, "Retail Pricing and Clearance Sales: The Multiple Product Case." *Journal* *of Economics and Business* 50: 551-563.

Gallant, A. R. and D. W. Jorgenson, 1979, "Statistical Inference for a System of Simultaneous, Nonlinear, Implicit Equations in the Context of Instrumental Variable Estimation." *Journal of Econometrics* 11: 275-302.

Gasmi, F., J. J. Laffont, and Q. H. Vuong, 1992, "An Econometric Analysis of Collusive Behavior in a Soft-Drink Market." *Journal of Economics and Management Strategy* 1: 277-311.

Genesove, D. and W. Mullin, 1998, "Testing Static Oligopoly Models: Conduct and Cost in the Sugar Industry, 1890 - 1914." *Rand Journal of Economics* 29: 355-377.

Giulietti, M. and M. Waterson, 1997, "Multiproduct Firms' Pricing Behaviour in the Italian Grocery Trade." *Review of Industrial Organization* 12: 817-32.

Greene, W., 2000, *Econometric Analysis*, 3rd ed. Upper Saddle River, Prentice-Hall.

Gupta, S., 1988, "Impact of Sales Promotions on When, What, and How Much to Buy." *Journal of Marketing Research* 25: 342-355.

Hansen, L. P., 1982, "Large Sample Properties of Generalized Methods of Moments Estimators." *Econometrica* 50: 1029-1054.

Hendel, I. and A. Nevo, 2002, "Measuring the Implications of Sales and Consumer Stockpiling Behavior." Paper presented at *Estimation of Dynamic Demand Models* seminar. Yale University, November.

Hess, J. D. and E. Gerstner, 1987, "Loss Leader Pricing and Rain Check Policy." *Marketing Science* 6: 358-374.

Hosken, D. and D. Reiffen, 2001, "Multiproduct Retailers and the Sale Phenomenon" *Agribusiness: An International Journal* 17: 115-137.

Hosken, D., D. Reiffen, 2004, "Patterns of Retail Price Variation." *RAND Journal of Economics* 35: 128-146.

Hosken, D. and J. D. Simpson, 2001, "Have Supermarket Mergers Raised Prices? An Event Study Analysis." *International Journal of the Economics of Business* 8: 329-342.

Kadiyali, V., P. Chintagunta, and N. Vilcassim, 1999, "Product Line Extensions and Competitive Market Interactions: An Empirical Analysis." *Journal of Econometrics* 89: 339-363.

Lach, S. and D. Tsiddon, 1996, "Staggering and Synchronization in Price-Setting: Evidence from

Multiproduct Firms." *American Economic Review* 86: 1175-1196.

Lal, R. and C. Matutes, 1994, "Retail Pricing and Advertising Strategies." *Journal of Business* 67: 345-370.

Levy, D., M. Bergen, S. Dutta, and R. Venable, 1997, "The Magnitude of Menu Costs: Direct Evidence from Large U.S. Supermarket Chains." *Quarterly Journal of Economics* 112: 791-825.

MacDonald, J., 2000, "Demand, Information, and Competition: Why Do Food Prices Fall at Seasonal Demand Peaks?" *Journal of Industrial Economics* 48: 27-45.

McAfee, R., 1995, "Multiproduct Equilibrium Price Dispersion." *Journal of Economic Theory* 67: 83-105.

McFadden, D., 1974, "The Measurement of Urban Travel Demand." *Journal of Public Economics* 3:303-328.

McLaughlin, E. W., K. Park, D. J. Perosio, and G. M. Green, 1999, "FreshTracks 1999: The New Dynamics of Produce Buying and Selling." Department of Agricultural, Resource, and Managerial Economics, Cornell University.

Narasimhan, C., 1988, "Competitive Promotional Strategies." *Journal of Business* 61: 427-449.

Neslin, S. A., C. Henderson and J. Quelch, 1985, "Consumer Promotions and the Acceleration of Product Purchases." *Marketing Science* 4:147-165.

Nevo, A., 2001, "Measuring Market Power in the Ready-to-Eat Cereal Industry," *Econometrica*, 69, 307-342.

Nijs, V. R., M. G. Dekimpe, J.-B. E. M. Steenkamp and D. M. Hanssens, 2001, "The Category Demand Effects of Price Promotions." *Marketing Science* 20: 1-22.

Pauwels, K., D. M. Hanssens, and S. Siddarth, 2002, "The Long-Term Effects of Price Promotions on Category Incidence, Brand Choice and Purchase Quantity." *Journal of Marketing Research* 39: 421-439.

Pesendorfer, M., 2002, "Retail Sales: A Study of Pricing Behavior in Supermarkets." *Journal of Business* 75: 33-66.

Pick, D.H., J. Karrenbrock, and H.F. Carman, 1990, "Price Asymmetry and Marketing Margin Behavior: An Example for California-Arizona Citrus." *Agribusiness: An International Journal* 6:75-84.

Powers, N. J., 1995, "Sticky Short-Run Prices and Vertical Pricing: Evidence from the Market for Iceberg Lettuce." *Agribusiness: an International Journal* 11: 57-75.

Slade, M. E., 1995, "Product Rivalry with Multiple Strategic Weapons: An Analysis of Price and Advertising Competition." *Journal of Economics and Management Strategy* 4: 445-476.

Sudhir, K., 2001, "Structural Analysis of Manufacturer Pricing in the Presence of a Strategic Retailer." *Marketing Science* 20: 244-264.

United States Department of Agriculture. National Agricultural Statistics Service. Market News Service Washington, D.C. various issues.

United States Department of Labor. Bureau of Labor Statistics. Employment, Hours, and Earnings from the Current Employment Statistics Survey. Washington, D.C. various issues.

Varian, H., 1980, "A Model of Sales" *American Economic Review* 70: 651-659.

Villas-Boas, J. M., 1995, "Models of Competitive Price Promotions: Some Empirical Evidence from the Coffee and Saltine Crackers Markets." *Journal of Economics and Management Strategy* 4: 85-107.

Villas-Boas, J. M. and R. S. Winer, 1999, "Endogeneity in Brand Choice Models." *Management Science* 445: 1324-1338.

Villas-Boas, J. M. and Y. Zhao, 2003, "The Ketchup Marketplace: Retailers, Manufacturers, and Individual Consumers." Working paper, Haas School of Business, University of California at Berkeley, May.

Villas-Boas, S., 2003, "Vertical Contracts Between Manufacturers and Retailers: An Empirical Analysis." Working paper, Department of Agricultural and Resource Economics, University of California at Berkeley, May.

Ward, R.W., 1982, "Asymmetry in Retail, Wholesale, and Shipping Point Pricing for Fresh Vegetables." *American Journal of Agricultural Economics*; 64:205-212.

Warner, E. and R. Barsky, 1995, "The Timing and Magnitude of Retail Store Markdowns: Evidence From Weekends and Holidays." *Quarterly Journal of Economics* 101: 321-352.

Werden, J., 1998, "Demand Elasticities in Antitrust Analysis." *Antitrust Law Journal* 66: 363-414.

White, H., 1980, "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica* 48: 817-838.

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	0.000	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 ($/lb.)	3328	2.428	1.941	0.000	14.471
Proportion of Products on Sale	3328	0.170	0.376	0.000	1.000
Number of Sale Products	3328	4.077	3.119	0.000	17.000
Wholesale Price ($/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. Structural Nested Logit Model of Sales Behavior: L.A. Supermarket Chains

Demand Equation			**Price Response**			**Sale Products**		
Variable	**Estimate**	**t-ratio**	**Variable**	**Estimate**	**t-ratio**	**Variable**	**Estimate**	**t-ratio**
Chain 1[a]	-0.485*	-5.319	**Chain 1**	9.523*	4.412	**Chain 1**	-3.856	-0.258
Chain 2	-0.023	-0.245	**Chain 2**	9.689*	4.490	**Chain 2**	-2.394	-0.160
Chain 3	0.057	0.567	**Chain 3**	10.772*	4.696	**Chain 3**	-2.991	-0.201
Chain 4	0.077	0.067	**Chain 4**	10.007*	4.638	**Chain 4**	-2.627	-0.176
Product 1	-0.287*	-3.377	**Product 1**	-2.879*	-4.712	**Product 1**	-1.351	-1.737
Product 2	-1.009*	-13.291	**Product 2**	-2.823*	-4.658	**Product 2**	0.978	1.326
Product 3	-0.398*	-5.999	**Product 3**	-1.402*	-2.317	**Product 3**	0.419	0.600
Product 4	-0.433	-6.741	**Product 4**	-1.152*	-1.988	**Product 4**	0.444	0.642
Product 5	-0.764	-9.570	**Product 5**	-2.457*	-4.041	**Product 5**	1.196	1.628
Product 6	-0.822*	-10.301	**Product 6**	-1.922*	-3.231	**Product 6**	1.372	1.194
Product 7	1.535*	29.131	**Product 7**	-2.705*	-3.788	**Product 7**	-9.569*	-11.135
Season 1	0.229*	8.948	**Season 1**	3.552*	8.861	**Season 1**	2.791*	6.302
Season 2	0.059*	2.326	**Season 2**	2.565*	6.116	**Season 2**	2.218*	5.050
Season 3	-0.136*	-4.981	**Season 3**	0.989*	3.566	**Season 3**	2.220*	5.318
$\boldsymbol{d}_{ij}$	1.853*	14.745	$\boldsymbol{v}_1$	0.017	1.253	$\boldsymbol{v}_5$	0.155*	3.286
$\boldsymbol{d}_{ij}\boldsymbol{p}_{ij}$	-0.055*	-4.482	$\boldsymbol{v}_2$	0.059	0.237	$\boldsymbol{v}_6$	-0.195*	-2.307
$\boldsymbol{p}_{ij}$	0.329*	21.337	$\boldsymbol{v}_3$	0.154	1.745	$\boldsymbol{v}_7$	-0.130*	-3.765
σ_I	0.912*	123.371	$\boldsymbol{v}_4$	20.569*	13.206	$\boldsymbol{v}_8$	17.242*	10.583
σ_J	0.254*	16.570	ϕ_1	1.397*	65.317	ψ	123.691	0.828
			ϕ_2	1.596*	88.547	γ_1	0.572*	9.312
			ϕ_3	1.108*	60.469	γ_2	0.295*	5.087
			ϕ_4	1.153*	57.614	γ_3	0.438*	8.456
						γ_4	0.359*	7.096
R^2								
χ^2	1,722.359							

[a] In this table, $d_{i,j}$ is a binary indicator variable that takes a value of 1 if the product is on price-promotion during a particular week, $d_{i,j}p_{i,j}$ is an interaction term between the promotion indicator and retail price, $p_{i,j}$ is the shelf-price, 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 test of that compares the minimized GMM 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 (64). The critical value for this test at a 5% level is 83.675.

Table 3. 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	1.000	1.513*	1.745*	1.150*
	N.A.	(88.547)	(60.469)	(57.614)
p_2	0.635*	1.000	1.247*	1.431*
	(65.317)	N.A.	(60.469)	(57.614)
p_3	0.564*	1.418*	1.000	1.271*
	(65.317)	(88.547)	N.A.	(57.614)
p_4	0.511*	1.286*	1.005*	1.000
	(65.317)	(88.547)	(60.469)	N.A.

	Response of:			
With Respect to:	n_1	n_2	n_3	n_4
n_1	1.000	0.293*	0.224*	0.287*
	N.A.	(5.087)	(8.456)	(7.096)
n_2	0.576*	1.000	0.277*	0.289*
	(9.312)	N.A.	(8.456)	(7.096)
n_3	1.119*	0.573*	1.000	0.561*
	(9.312)	(5.087)	N.A.	(7.096)
n_4	0.717*	0.367*	0.281*	1.000
	(9.312)	(5.087)	(8.456)	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 the proportion of sale products in chain *i* with respect to a change in the proportion of products offered on sale in chain *j* in the upper and lower panels, respectively. For all elasticity estimates, a single asterisk indicates significance at a 5% level.

Table 4. 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	-4.468	1.121	1.121	1.121	1.121	1.121	1.121	1.121
	p_2	0.381	-4.414	0.381	0.381	0.381	0.381	0.381	0.381
	p_3	0.937	0.937	-7.881	0.937	0.937	0.937	0.937	0.937
	p_4	0.472	0.472	0.472	-10.361	0.472	0.472	0.472	0.472
	p_5	0.317	0.317	0.317	0.317	-4.782	0.317	0.317	0.317
	p_6	0.252	0.252	0.252	0.252	0.252	-6.652	0.252	0.252
	p_7	9.953	9.953	9.953	9.953	9.953	9.953	-17.579	9.953
	p_8	0.142	0.142	0.142	0.142	0.142	0.142	0.142	-14.166
Chain 2	p_1	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079
	p_2	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024
	p_3	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060
	p_4	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063
	p_5	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021
	p_6	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029
	p_7	1.266	1.266	1.266	1.266	1.266	1.266	1.266	1.266
	p_8	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029
Chain 3	p_1	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096
	p_2	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
	p_3	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045
	p_4	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039
	p_5	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032
	p_6	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021
	p_7	1.528	1.528	1.528	1.528	1.528	1.528	1.528	1.528
	p_8	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042
Chain 4	p_1	0.110	0.110	0.110	0.110	0.110	0.110	0.110	0.110
	p_2	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007
	p_3	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070
	p_4	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064
	p_5	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016
	p_6	0.034	0.034	0.034	0.034	0.034	0.034	0.034	0.034
	p_7	1.508	1.508	1.508	1.508	1.508	1.508	1.508	1.508
	p_8	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049

[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 5. 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	-4.088	-4.456	-0.081	-0.003	0.452
1	2	-4.013	-4.432	-0.032	-0.001	0.452
1	3	-7.538	-7.916	-0.072	-0.002	0.452
1	4	-9.987	-10.400	-0.038	-0.001	0.452
1	5	-4.376	-4.800	-0.026	-0.001	0.452
1	6	-6.245	-6.675	-0.021	-0.001	0.452
1	7	-17.882	-17.745	-0.563	-0.027	0.452
1	8	-13.773	-14.215	-0.009	0.000	0.452
2	1	-2.334	-3.539	-0.058	-0.004	1.266
2	2	-2.919	-4.165	-0.019	-0.001	1.266
2	3	-7.617	-8.833	-0.046	-0.003	1.266
2	4	-9.032	-10.248	-0.047	-0.003	1.266
2	5	-2.207	-3.456	-0.016	-0.001	1.266
2	6	-4.238	-5.482	-0.022	-0.001	1.266
2	7	-15.130	-15.722	-0.608	-0.067	1.266
2	8	-22.803	-24.055	-0.013	-0.001	1.266
3	1	-3.643	-4.443	-0.071	-0.005	0.876
3	2	-5.078	-5.948	-0.006	0.000	0.876
3	3	-9.922	-10.762	-0.033	-0.002	0.876
3	4	-10.279	-11.125	-0.028	-0.002	0.876
3	5	-4.010	-4.859	-0.026	-0.002	0.876
3	6	-5.831	-6.692	-0.015	-0.001	0.876
3	7	-11.042	-11.298	-0.540	-0.080	0.876
3	8	-34.310	-35.165	-0.020	-0.001	0.876
4	1	-2.973	-4.003	-0.078	-0.006	1.113
4	2	-5.541	-6.652	-0.003	0.000	1.113
4	3	-8.538	-9.594	-0.054	-0.004	1.113
4	4	-9.269	-10.331	-0.048	-0.003	1.113
4	5	-4.451	-5.552	-0.011	-0.001	1.113
4	6	-5.297	-6.382	-0.026	-0.002	1.113
4	7	-15.028	-15.409	-0.648	-0.085	1.113
4	8	-26.434	-27.516	-0.029	-0.002	1.113

[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.