Assessing the Impact of Retailer Store Brand Presence on Manufacturer Brands in a Equilibrium Framework[†]

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Abstract

This article assesses the impact of retailer own-labeled products on manufacturer brand prices, profitability, and consumer welfare. Using chain-level retail scanner data from Boston's white fluid milk market the analysis estimates a random coefficients logit demand model employing a mathematical programming equilibrium constraint(MPEC) method. One can compute profit margins implied for a set of pricing games using estimated demand parameters. Nonparametrically identified non-nested tests identify the most likely pricing game for the Boston white fluid milk market. Results from this analysis indicate that branded milk manufacturers are Stackelberg leaders to retailers and store brand milks are procured at or near cost. This baseline model of the market is matched against a series of counterfactual markets to assess the impact of strong store brands. One counterfactual simulation considers the absence of the leading retailer's own labeled milk. Another considers the market without store brand milks. Simulation results indicate that strong store brands increase channel profits, retailer profits, and consumer welfare, while having mixed ef-

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fects on equilibrium manufacturer brand retailer prices. In addition results testify that with no store brand milk consumer welfare is approximately 11.5% lower.

1 Introduction

This article employs a structural approach to analyze the vertical relationships of retailers and manufacturers and to evaluate the effect of store brands on pricing, profits, and consumer welfare in an equilibrium framework. Using chain level Information Resources Inc data for Boston we analyze two brands and each chain's store brand. The data are monthly from March 1996 to July 2000. First we estimate demand parameters for the flexible random coefficient logit demand model of Berry, Levinsohn, and Pakes (1995). Using the demand parameter estimates one can calculate the retailer and manufacturer margins implied by alternative supply channel pricing models. Subtracting these margins from prices provides channel cost values for each of the alternative supply scenarios. Then one uses input prices to estimate the cost function for each possible supply model to determine the statistically favored channel pricing model. Next we simulate two counterfactuals to analyze the strategic impact of store brands. This exercise shows how retail prices, retail profits, manufacturer profits, market shares, and consumer surplus change when store brand provision changes.

Theoretical research predicts that the marketing of store brands by retailers eliminates double marginalization, reduces retail prices on leading brands, and increases channel profits and consumer welfare (Scott-Morton & Zettelmeyer, 2001). Mills (1995) presents a rigorous model that demonstrates store brands are instruments for a retailer to overcome the well-known double marginalization problem present in distribution channels. Store brand provision allows the retailer to extract profit from the vertical channel and lower prices. Steiner (2004) similarly argues that the unique position of store brands constrain the market power of national brands in ways that their horizontal competitors cannot. Moreover, he postulates that the vertical competition between store and national brands has a consumer welfare improving effect via a consumer surplus improving decrease in retail prices and stimulation of innovation. Steiner (1993) also describes a vertical structure where store brands improve retailer and consumer welfare.

Empirical support for these theories are sparse. Raju, Sethuraman, and Dhar (1995) find that store brands increase category profits for retailers. They conclude that this is particularly the case when a category has several national brands. Chintagunta and Bonfrer (2002) examine the introduction of a store brand into a category by estimating demand conditions before and after introduction at a single retailer. They observe wholesale prices paid by the retailer and use them to gain intuition on retailer conduct in the market. For demand they investigate the changes in preferences under the two market regimes, before and after the introduction of the store brand. On the supply side they measure the effects of the new entrant's store brand on the actions between retailer and manufacturer. However they use a conduct parameter approach and do not explicitly formulate and test channel pricing models.[1]

Recent advances in vertical channel modeling allow us to determine the nature of the vertical pricing game manufacturers and retailers are playing. Much of the work on store brand pricing analyze retail price elasticities without explicitly modeling how brand manufacturers wholesale pricing moves are linked by some form of retailer pricing conduct to retailer pricing moves.

Sudhir (2001) working on the yogurt and peanut butter markets, highlights the need to accurately model vertical strategic interaction along with horizontal strategic interaction when using retail level data. Villas-Boas and Zhao (2005) investigate the ketchup market in a Texas city and demonstrate the bias that results by ignoring endogeneity of demand, and model the supply side with the profit maximizing decision of retailers and manufacturers. Bonnet and Dubois (2010) empirically investigate vertical contracts between retailers and manufactures using retail data on bottled water collected from retail chains in France. They extend previous work by considering non linear vertical contracts that model two part tariffs with and without retail price maintenance. Villas-Boas (2007) outlines conditions that allow data on retail price, retail quantities and input prices at the two stages in the market channel to identify retailers' and manufacturers' vertical pricing conduct. This method allows one to investigate interactions in the market channel using retail level prices without observing wholesale prices.

The research conducted in this article improves our understanding of how the supply channel works in two ways. This is the first research to use a vertical structural model of the supply channel to investigate empirically how store brand presence effects vertical relationships between retailers and manufactures. Second, it investigates a robust cross section of firms to determine how store brand presence effects vertical and horizontal relationships between retailers and manufacturers. This research analyzes vertical conduct in a market that has four retail chains, a total of 187 locations, each chain with a store brand, and two major brand manufactures that sell in all four retailers. In concert our developments provide a broader empirical

[1] See Corts (1998) for critiques of conduct parameter approaches.

analysis of store brand presence that includes vertical and horizontal interactions. Consequentially we conduct a more robust investigation on the validity of assertions made in the theoretical literature about the role store brand presence plays in the channel between retailers and manufacturers as well as among each.

As an additional contribution we outline conditions for the non-parametric identification of the non-nested tests we employ to determine the most empirically relevant model of the supply channel. We discover that one requires exogenous variation in both retailer and manufacturer markups to achieve full identification. Unlike earlier work the data we employ includes variation in both exogenous retailer specific characteristics and exogenous manufacturer specific characteristics. Independent variation from these two sources generates exogenous variation in both retailer and manufacturer markups, hence our non-nested test are identified.

The remainder of this paper is organized as follows. Next we introduce the demand model and estimation approach. The third section derives retail and manufacturer implied margins, presents alternative models of channel supply, and describes a test for model selection. The fourth section presents the data, estimation results, and model selection results. In the fifth section we describe counterfactual simulations and compare the selected model equilibria to the counterfactual equilibria. Finally, concluding remarks and suggestions for extending the research are made.

2 Demand Specification and Estimation Approach

This section specifies the random coefficients logit demand model, and describes the models implied price response function that is applied in the next section to determine optimal markups.[2] Finally it explains the mathematical programming equilibrium condition (MPEC) estimation approach, introduced by Dube, Fox, and Su (2009) that we use for estimation.

2.1 Random Coefficients Logit

The random coefficients logit allows consumers to differ in tastes for product characteristics. We specify the following linear version of the random utility model:

$$V_{ij} = C_j \beta^i - \alpha^i p_j + \eta_j + \epsilon_{ij}. \tag{1}$$

[2]We acknowledge the editor Saul Lach and two anonymous reviewers for suggesting we use this demand model in lieu of the nested logit which unreasonably constrains implied profit margins.

i indexes individuals and j indexes products. A product is defined as a unique brand - retailer combination. C are product characteristics and p is price. β is marginal utility for product characteristics and α is marginal utility of income. η_j is an aggregate product demand shock, or in other words, a time varying product attribute unobserved by the econometrician. It is assumed that ϵ_{ij} are distributed *i.i.d.* according to an extreme value type I distribution. There are J products and a zero utility outside option. $[\beta^i, \alpha^i] \equiv \theta^i$ are marginal utility parameters assumed to vary over consumers and follow independent normal distributions, $\theta^i \sim N(\bar{\theta}, \Sigma)$. Σ is consequently diagonal and coefficients are allowed to have different variance. In the following we group C and p into a single vector X.

The market share of product j as a function of the total group share is:

$$\begin{aligned} s_j &= \int s_{ij}\phi(\theta^i|\bar{\theta}, \Sigma)d\theta^i \\ &= \int \frac{exp(X_j\theta^i + \eta_j)}{1 + \sum_k exp(X_k\theta^i + \eta_k)}\phi(\theta^i|\bar{\theta}, \Sigma)d\theta^i. \end{aligned} \tag{2}$$

where k indexes the products in all retailers and ϕ is the multivariate normal density. Market share can be expressed in terms of mean utility, observing that $\theta^i = \bar{\theta} + \nu_i$, where $\nu_i \sim N(\mathbf{0}, \Sigma)$, s_j can be written as:

$$s_j = \int \frac{exp(\mu_j + X_j\nu_i)}{1 + \sum_k exp(\mu_k + X_k\nu_i)}\phi(\nu_i|\mathbf{0}, \Sigma)d\nu, \tag{3}$$

where $\mu_j = X_j\bar{\theta} + \eta_j$.

2.2 Demand Response to Price

The random coefficients logit introduces heterogeneity in consumer tastes so the model empirically and theoretically flexible (McFadden & Train, 2000). Individual consumer shares are, $s_{ij} \equiv exp(X_j\theta^i + \eta_j + \epsilon_{ij})/1 + \sum_k exp(X_k\theta^i + \eta_k + \epsilon_{ik})$. The own and cross-price responses of market shares, s_j, to a change in price, p_k, are:

$$\frac{\partial s_j}{\partial p_k} = \begin{cases} -\int \alpha^i s_{ij}(1 - s_{ij})\phi(\nu_i)d\nu_i, & \text{for } j = k; \\ \int \alpha^i s_{ij}s_{ik}\phi(\nu_i)d\nu_i, & \text{for } j \neq k. \end{cases} \tag{4}$$

Equation 4 generates price elasticities that are driven by consumer specific marginal utilities, θ^i. The random coefficient logit model captures consumer switching due to similarities in consumers tastes for product characteristics. Because consumers with similar tastes make similar choices, aggregating their individual responses yields market elasticities that appreciate product characteristics as determinants of switching behavior.[3] However, it is important to note that the random coefficients logit does not eliminate IIA at the consumer level. The degree to which IIA is ameliorated at the aggregate level is an empirical question that has only been considered in recent work by Cohen (2009). Most importantly the margins implied by the random coefficient logit are free to vary across products, and do so according to product similarities or differences.

2.3 Estimation Approach

Under weak regularity conditions on the density of consumer unobservables, the existence of a unique mean utility that satisfies the observed market shares has been established by Berry (1994). This fact allows one to use the condition that observed market shares must equal predicted market shares when consumer utility parameters are estimated. Previous empirical analysis has relied on the nested fixed point approach to estimate the random coefficients logit model (Berry et al., 1995; Nevo, 2001; Villas-Boas, 2007; Bonnet & Dubois, 2010). The nested fixed point estimation approach is made up of two distinct parts. First practitioners use contraction mapping to find the mean utility that makes observed share equal to predicted shares. Then they estimate the density of preference parameters in a subsequent step using a GMM approach. The MPEC approach of Dube et al. (2009) recast estimation of the random coefficients logit as a mathematical programming problem with equilibrium constraints. In their approach they specify the same highly nonlinear GMM function and minimize it with the constraint that observed market shares equal predicted market shares using state of the art optimization tools such as $KNITRO^{®}$.[4]Dube et al. (2009) document several numerical concerns for the nested fixed point approach typically applied in the literature, and demonstrate that the constrained optimization approach is uniformly preferred.

3 Structural Model of the Supply Channel

This section introduces the supply models tested as candidates for the Boston fluid milk marketing supply channel. Strategic profit maximization is modeled at both the retail and manufacturer levels of the supply

[3]Alternative logit specifications such at the representative consumer logit and nested logit constrain price response so that, when Nash Bertrand pricing is assumed, retailers apply the same markup to all products in the category (nests).

[4]We use the estimation code of Dube et al. (2009) to estimate our model. It is available from the authors upon request.

chain. Farmers supply milk to fluid processors at an exogenously set federal milk market order price. Raw milk is therefore assumed to be secured from a competitive input market. First we derive profit maximizing margins for retailers and then for manufacturers given retail pricing. After deriving optimal channel margins we describe the set of six pricing games tested as candidates for the Boston fluid milk market.

3.1 The Retail Market

Assume there are N Nash Bertrand multi-product oligopolists competing in a retail market and each retailer maximizes category profit for sale of all branded and own-labeled fluid milk products. Each retailer's milk profit function in time period t takes the form:

$$\pi_{rt} = \max_{p_{jt} \forall j \in \mathfrak{S}_{rt}} \sum_{j \in \mathfrak{S}_{rt}} [p_{jt} - p^w_{jt} - c^r_{jt}] s_{jt}(p).$$

$\mathfrak{S}_{rt}$ is the set of products sold by retailer r during week t, w indexes manufacturers, j and k index products. The first order condition, assuming a pure strategy Nash equilibrium in price, is:

$$s_{jt} + \sum_{k \in \mathfrak{S}_{rt}} [p_{kt} - p^w_{kt} - c^r_{kt}] \frac{\partial s_{kt}}{\partial p_{jt}} = 0. \tag{5}$$

The first order conditions can be stacked into a system of equations for each product at each retailer. The terms may be rearranged to solve for retailer margins. This linear system can be expressed in matrix notation:

$$p_t - p^w_t - c^r_t = -(T_r \times_{elt} \triangle_{rt})^{-1} s_t(p). \tag{6}$$

T_r is a matrix of ones and zeros that captures the products in the set $\mathfrak{S}_{rt}$ by executing element-wise multiplication, $\times_{elt}$. In other words the retailers maximize their profits over products in their portfolio, hence it's called the ownership matrix. Element $T_r(k, j) = 1$ if a retailer has both products k and j in their portfolio, and $T_r(k, j) = 0$ otherwise. $\triangle_{rt}$ is a matrix containing the derivatives of share with respect to retail price. This matrix is called the retailer response matrix and has the typical element $\frac{\partial s_j}{\partial p_k}$, appearing in equation 4.

3.2 Manufacturer

Assuming that manufacturers set wholesale price upon observing retail price the manufacturer's profit maximization problem is written as:

$$\pi_{wt} = \max_{p_t^w \forall j \in \mathfrak{S}_{wt}} \sum_{j \in \mathfrak{S}_{wt}} [p_{jt}^w - c_{jt}^w] s_{jt}(p(p^w)).$$

Here $\mathfrak{S}_{wt}$ is the set of products sold by manufacturer w during week t. The resulting first order condition is:

$$s_{jt} + \sum_{m \in \mathfrak{S}_{wt}} [p_{mt}^w - c_{mt}^w] \frac{\partial s_{mt}}{\partial p_{jt}^w} = 0. \tag{7}$$

The manufacturer ownership matrix T_w is defined in the exact way that the retail ownership matrix is. The elements of the manufacturer response matrix, $\triangle_{wt}$, are the derivatives of product market share with respect to wholesale price, i.e. $\frac{\partial s_j}{\partial p_i^w}$. The matrix $\triangle_{wt}$ contains the cross price elasticities of demand and the effects of cost pass through, these effects can be decomposed in the following manner by evoking the chain rule:

$$\triangle_{wt} = \triangle_{pt}' \triangle_{rt}.$$

Here $\triangle_{pt}$ represents the cost pass through and $\triangle_{rt}$ contains own and cross price sensitivities of market share to retail price changes. $\triangle_{rt}$ was introduced in the previous subsection. The matrix $\triangle_{pt}$'s elements are the derivatives of all retail prices with respect to all wholesale prices, and have the general element $\triangle_{pt}(k,j) = \frac{\partial p_j}{\partial p_k^w}$.

The elements of the matrix $\triangle_{pt}$ are derived by totally differentiating, for a given product j, the retailer first order condition in equation 5:

$$\sum_{k=1}^{N} \underbrace{[\frac{\partial s_j}{\partial p_k} + \sum_{i=1}^{N} (T_r(i,j) \frac{\partial^2 s_i}{\partial p_j \partial p_k} (p_i - p_i^w - c_i^r)) + T_r(k,j) \frac{\partial s_k}{\partial p_j}]}_{g(j,k)} dp_k - \underbrace{T_r(f,i) \frac{\partial s_f}{\partial p_j}}_{h(j,f)} dp_f^w = 0.$$

Stacking these conditions for all $j = 1, 2, ..., N$ products together into a linear system, one has:

$$Gdp - H_f dp_f^w = 0.$$

The matrix G has general element $g(j,k)$, and H_f is an N-dimensional vector with general element $h(j,f)$. Rearranging terms implies the vector:

$$\frac{dp}{dp_f^w} = G^{-1}H_f.$$

Horizontally concatenating H_f together for all products j, one has the desired matrix,

$$\triangle_p = G^{-1}H.$$

Collecting terms and solving equation 7 for the manufacturers' implied price-cost margins gives us:

$$p_t^w - c_t^w = -(T_w \times_{elt} \triangle_{wt})^{-1} s_t(p). \tag{8}$$

3.3 Supply Channel Structures Considered

We confine our analysis to the four largest supermarket retailers and two largest brand manufacturers of white fluid milk in Boston. Six distinct structural models of linear channel pricing conduct are defined. Specification of the ownership matrices, T_r and T_w, determine the alternative forms of channel conduct. For each channel structure the retailer and manufacturer response matrices defined in the previous section remain unchanged. Each model of channel pricing is presented in turn along with the empirical motivation for including it in the set we test.

In the first channel structure retailers set margins by maximizing profits over the set of products in their portfolio according to equation 6. Manufacturers set margins upon observing the retailer's price response function. This is a Manufacturer Stackelberg pricing game. The pair of optimal margins that identifies the pricing game are given by equations 6 and 8. The ownership matrices that give rise to these implied margins have element $T(k,j) = 1$ if a firm has both products k and j in their portfolio, and $T(k,j) = 0$ otherwise. This pricing game is characterized by manufacturer margins that are larger than retailer margins for a given milk product sold in their store. This game includes a store brand manufacturer that maximizes profit independent of the retailer they package for in the same way leading manufacturer brands do. All the retailers except Stop & Shop procure their store brand milk from independent manufacturers. The empirical question is therefore whether store brand manufacturers independently secure a margin consistent with oligopolistic pricing behavior.

The second structure has only manufacturers of the branded products, Hood and Garelick, as channel Stackelberg leaders. Store brand manufacturers supply milk to retailers competitively. This implies that the retail ownership matrix is the same as the first structure. The manufacturer ownership and response matrix now simply omit rows and columns corresponding to store brand products. Store brand milk is procured by retailers at manufacturer cost. This model is consistent with retailer integration into the manufacturing process by manufacturing its own store brand, such as Stop & Shop was doing during the period we study, or simply that the retailer is able to buy own labeled milk at or very close to cost from a manufacturer. The latter scenario is typical when a branded manufacturer's processing plant wants to ensure that it is running at capacity. This practice effectively increases manufacturer margins on the branded products they market by keeping per unit cost of production lower with economy of scale. Steiner (2004, p.113) cites research on private milk bargaining where this has been the case.

The third structure specifies a model of manufacturer domination where store brands remain integrated. In this structure brand manufacturers horizontally collude. This implies that the colluding entity has joint ownership over all manufacturer branded products in the market, consequently the manufacturer ownership matrix omits rows and columns corresponding to store brand products and is unity for each remaining element. The retailer ownership matrix is unchanged. The third structure is consistent with tacit collusion between the two brand manufacturers, Hood and Garelick.

The forth structure we test assumes that profits are maximized once, at retail. This structure is consistent with channel coordination wherein retailers and manufacturers overcome double marginalization and divide the windfall profit into negotiated proportions. This may include strict domination by either retailers or manufacturers, or coordination by a channel captain. This is achieved from a modeling standpoint as setting $p_t^w = c_t^w$, therefore the manufacturer's profit maximizing margins are omitted. Definition of the retail ownership matrix continues to be unchanged; appreciating the fact that the windfall is divided as we describe above. Many supermarkets employ independent category managers to work with brand manufacturers, supermarkets around Boston are no exception. Category managers work with brand representatives to determine pricing, promotion, and placement of products on the retailer's shelves. This practice potentially gives rise to tacit coordination consistent with the fourth structure.

The fifth structure assumes that retailers collude, private label is integrated, and brand manufacturers play the Stackelberg leader role. This implies that the retailer ownership matrix is unity for each and every element. The manufacturer's ownership matrix is the same and omits rows and columns corresponding to store brand products as in the second structure. This structure is an extreme form of horizontal tacit collusion that is empirically less likely but should not be ruled out. As an empirical matter the market is dominated - in market share - by a single retailer, Stop & Shop, who could potentially lead other retailers to follow its pricing practices. Such a scenario is consistent with the fifth structure.

The sixth structure posits that Stop & Shop is integrated into the processing of its store brand milk and take as given brand manufacturer prices. The remaining retailers coordinate with the brand manufacturers maximizing prices at retail and dividing the windfall profits in the same way as structure four. It stands to reason that this is an empirically justified model because during the time frame for the data set we analyze Stop & Shop owned its own milk processing plant, meaning that it was more likely to engage in stiffer vertical competition with brand manufacturers than other retailers were. The fact that other retailers procured their store brands from one of the two brand manufacturers implies that more room is left for coordination though store brand procurement contracts. Structure six identifies margins that are consistent with stiffer vertical competition between Stop & Shop and the brand manufacturers, and tacit coordination between other retailers and brand manufacturers.

3.4 Determining the Model of Channel Conduct

Following the empirical analysis of Villas-Boas (2007) and Bonnet and Dubois (2010) we specify models of channel cost implied by the supply channel models from the previous section and conduct pairwise non-nested tests to identify the supply model that best explains the data generation process. First we derive models of channel marginal cost. Next we describe the identification properties of the non-nested tests, including a careful explain of why non-nested testing by previous work lacks non-parametric identification, and introduce a method to achieve non-parametric identification.

The margins can be specified in a model of channel pricing as:

$$p_{jt} = RM_{jt} + MM_{jt} + \overbrace{f(c_{jt}\gamma^{i})}^{ChannelCost} + \epsilon_{jkt}. \tag{9}$$

The implied margins can be subtracted from both sides of equation 9 to define a channel cost specification for each pricing game:

$$
\begin{aligned}
p_{jt} - RM_{ijt} - MM_{ijt} &= CC_{ijt} \\
&= f(c_{jt}\gamma^{i}) + \varepsilon_{ijt}. \qquad (10)
\end{aligned}
$$

This is the channel marginal cost model for pricing game i. RM is the retail margin and MM is the manufacturer margin.

Equation 10 highlights the fact that channel markup is the sum of three unobservables: Retailer markup, manufacturer markup, and channel marginal cost. If channel marginal cost is not observed testing models of supply conduct relies on assessing which functional forms of the retail margin, RM, and the manufacturer margin, MM, are best-fitting. The current analysis requires that there be some exogenous source of firm level variation in margins since firms do not behave symmetrically.[5] In other words one requires variation in firm profits independent of its competitors. This variation is what allows us to empirically distinguish between non-nested models of channel marginal cost, ultimately enabling determination of the best-fitting model.

The previous literature relies on variation in manufacturer product characteristics to identify margins. This practice is satisfactory for generating variation in manufacturer margins, however it does not appear that previous work exploits any source of exogenous variation in retailer specific characteristics. This fact brings into question whether models of channel marginal costs in previous work and consequently non-nested tests conducted by previous work are uniquely identified, at least in a non-parametric sense. To achieve non-parametric identification for non-nested tests of the sort we employ firm specific exogenous variation in margins is required.

The data we use to conduct empirical analysis is uniquely suited to overcome the identification issue we raise. To achieve full identification we include both exogenously determined manufacturer specific characteristics and exogenous retailer specific characteristics that vary over the data sample period. Both manufacturer and retailer margins are a function of these characteristics. Since margins are determined by market share we specify demand as a function of services that retailers offer to uniquely brand the assortment of products they sell in addition to the characteristics of the manufactured products themselves. As a consequence the non-nested tests we conduct achieve non-parametric identification.

[5] In equilibrium prices and markups are not equal across products.

The linear GMM estimator is applied to estimate channel cost models. The moments we specify exploit unconditional mean independence between input prices and the model error. We regress estimated channel marginal costs, calculated from each supply side game, on a set of proxies for retailer and manufacturer input price. For each retailer manufacturer pricing game the estimated marginal channel cost (left hand side of equation 11) will differ. The function $f(c\gamma)$ specifies that channel marginal costs are a function of input prices. We conduct tests for linear, generalized Leontief, exponential ($e^{c\gamma}$) and logarithmic ($ln(c\gamma)$) forms of the cost function. Alternative functional forms of channel marginal cost did not alter tests results, therefore we only report results for the linear functional form. To formally rank the supply side models we bootstrap a Smith (1992) Cox-type test statistic in the generalized moment framework. Non-nested tests such as Smith's have low power for data sets with few cross sectional components and moderate panel length. However since our data set consist of twelve cross sectional units, three milks at each of four retailers, over 58 quad-week periods, the data sample is particularly large, hence improving the power of the test in comparison to previous studies that apply it.

For the six competing models considered in this paper fifteen pairwise tests identify the best pricing game in the sense that it explains the data generation process better then the competing games. These non-nested tests are not transitive. For example assume that we are considering three models. If model 1 is chosen in favor of model 2 and 2 is chosen in favor of 3 it is not guaranteed that 1 is chosen in favor of 3. However if we only fail to reject a particular model and reject in favor of the same model we choose it as the benchmark factual market.

4 Data, Demand Estimates, and Model Selection Results

This section describes the data used for our empirical analysis. Next it interprets demand model estimation results. Then it reports the results from the non-nested tests for determining the most empirically relevant supply channel model.

4.1 Data

The Information Resources Inc.(IRI) Boston market level data for each of four chains used in this study has many chain level variables including prices and quantity, and it covers 58 quad week periods beginning

March 1996 and ending July 2000. The class one raw milk price data are from federal milk market order one publications. Data on supermarket characteristics for each chain come from Spectra Marketing and span the same time period as the scanner data in quarterly observations, this data set also reports a figure for sales per square foot. Per capita income and population data have been collected from annual editions of Market Scope. Data on electricity and diesel fuel cost are from the Energy Information Administration.[6]

Exploring chain level data implies uniform pricing behavior across retail outlets within a chain in a market such as Boston. Generally for an advertised product such as milk this is the case within a market area. Chains price uniformly to avoid the criticism that they are price gouging particular urban neighborhoods. We aggregate IRI stock keeping unit (sku) data to the brand level for each chain.[7] We control for the impact of package size differences on demand by including a units per volume variable in our demand specification. Aggregation over different fat levels, for a given brand of white fluid milk is a reasonable practice because the retailers we consider engage in flat pricing of milk across fat levels (Cotterill, Rabinowitz, Cohen, Murphy, & Rhodes, 2007).

The same brands at different retailers are different products. For this reason our demand specification includes attributes of the retail chain as a characteristic of the products purchased in that retail chain. Using Spectra Marketing data one has the following retailer characteristics: pharmacy, bank, fresh fish counter, deli, and salad bar. This approach recognizes that a chain can brand it self by developing a unique array of services and products including a broad high quality line of store brands. Also chain specific data generate exogenous variation in retail margins that permit us to identify the non-nested tests of channel pricing conduct. Bonnano and Lopez (2009) report that the consumer demand for fluid milk is influenced by one stop shopping attributes of supermarkets including breadth and depth of services offered. In the Spectra data one knows whether a specific store in the Boston market has the service or not. Using this information one can calculate the proportion of stores in the chain offering the service in each time period. Due to collinearity in the service data we use principal component analysis to identify two orthogonal services. To generate a non-food service variable we take the product of the propensity measures for those services, the same procedure is executed to generate a food service variable.

Table 1 reports summary statistics for chain specific brand price, market shares, and group shares.

[6]Spectra Marketing is a sister company of A. C. Nielsen. All marketing data are available from the University of Connecticut, Food Marketing Policy Center.

[7]Skus identify package sizes and different products within a brand.

Hood has the highest per gallon prices across all chains followed by Garelick then private label. Among the retail chains Star Markets, located in the urban core, has on average the highest milk prices followed by Stop & Shop, Shaws, then Demoulas. Stop & Shop has the largest share of fluid milk sales with 18%, and they lead in store brand sales with 12.6% while Demoulas is a close second with 11.1%. Store brand dominates sales within Demoulas at 89.8% whereas Star markets store brand milk sales only make up 52.3%.

Table 2 has summary statistics for three other control variables. Weighted price reduction is a variable measuring price promotion of a given brand in the supermarket. It is the percent reduction in price from the suggested retail price when price is reduced. This variable controls for price promotional activities. The "share of skim to whole milk sold" controls for the aggregation of the different butter fat content milks which may influence demand if consumers are health conscious. A value greater than 1 reveals that a greater share of skim or low-fat milk was sold for the given product than whole. "Units per volume" which is the average number of units sold per gallon and controls for container size.

Table 3 reports the Spectra Marketing data on store characteristics for each chain. Stop&Shop had on average approximately 70 stores in the Boston metropolitan area during this period, Shaws had approximately 46, Demoulas 32 and Star 19. Stop&Shop's stores have the most retail space. Stop&Shop is also the leader in services especially in non-food services as compared to their competitors. Demoulas has the fewest services and Shaws and Star have similar amounts. Table 3 also has market level statistics for household income as well as channel input costs: the prices of raw milk, electric, and diesel. Note the typical price paid to farmers for a gallon of raw milk is \$1.40 effectively half of the retail price.

4.2 Empirical Specification and Parameter Estimates

Specifying the demand model requires that we compute market shares based on an exogenously determined market size. We consider three specifications of market share assuming each member of Boston's population consumes either four, six, or eight ounces of fluid milk each day. The evaluation of predicted market share requires the integration over the consumer distribution of preferences, as one observes in equation 3. Since this integral does not posses a closed form solution it must be simulated. To simulate the integral we draw 200 deviations from mean utility, ν, one for each simulated consumer. The literature commonly uses between 50 and 100 households (Nevo, 2001). Dube et al. (2009) suggest more be used and, given the computational efficiency of their approach, estimation that simulates the integral with 200 simulated consumers is feasible.

We use cost shifting variables excluded from the model to identify α, the coefficient on the endogenous price variable. These input prices are orthogonal to the structural error and correlated with price, consequently they are used to define moment conditions intended to identify α. The cost shifters we specify include: the price of raw milk multiplied by the brand indicator variables, price of electric and diesel as well as sales per square foot.[8]

Table 4 presents point estimates of average market tastes, $\bar{\theta}$, and standard errors for these estimates when the market is defined assuming six ounce servings. For the random coefficients logit model the table also includes estimates of the standard deviations in taste across consumers for each parameter and standard errors for these estimates. The marginal utility of income parameter, α, on price has the proper sign, adhering to the law of demand. The price reduction coefficient is located near zero indicating that price promotions have a minor impact on average consumption utility. An anonymous reviewer suggested that this variable may be endogenous and in fact endogeneity might explain this variable's weak results. The positive units per volume coefficient indicates consumer prefer smaller packages such as quart to half gallon and half gallon to gallon containers. The positive skim to whole ratio testifies that consumer prefer milk with less fat on average. However, Non-food services are utility improving for each milk product; more food services generate higher utility when consumers choose Hood, the premium brand, and lower utility for Garelick or a store brand.

The bottom of table 4 reports demand model parameter estimates under each assumed market size. This demonstrates the sensitivity of the price coefficient to market definition. Estimates are all fairly close and significant. We use estimates from each market size specification for the random coefficient logit model to compute demand elasticities. The left side of table 5 reports mean own-price elasticity as well as the average mean cross price elasticities over all competing products for the market sizes implied by four and eight ounce servings. The full mean elasticity matrix for the market implied by six ounce servings appears alongside. Results found in table 5 qualitatively verify, as an empirical matter, that the estimated demand elasticities are fairly robust to the market size specifications we consider. Going forward we will employ the six ounce specification.

[8]Interacting raw milk prices with brand dummies allows us to separate brand variation in prices due to differing production technologies employed for the processing of each milk product under consideration (Villas-Boas, 2007, p.637-38).

4.3 Supply Model Test

Table 6 displays results from the fifteen pairwise Smith tests. Bootstrapped test statistics were computed and appear in the table with lower tail p-values reported directly below. The Smith test is a lower tail test. The statistic is of the Cox-type and is best described as the difference in the GMM objective functions under the probability limit for the H_2 model. In a general sense the lower the GMM objective value the better the model. The test statistic is asymptomatically normal with mean zero.

Results testify that model two is favorable to model one and that model two is never rejected in favor of the other models under consideration. This is verified by observing the bold highlighted values in table 6. The statistic is significantly smaller than zero for model two as an alternative to model one and never significantly smaller than zero for model three through six. Model two posits brand manufacturers Hood and Garelick as channel Stackelberg leaders, retailers procure their private labels at or near cost, and retailers are category profit maximizers that take wholesale brand prices as given. That is we find that the manufacturers consider retailer reaction to any wholesale price that they set and the resulting retailer price for their product when determining their markup. The fact that retailers procure their store brand milk at cost is consistent with the fact that Stop & Shop processes its own store brand, so by virtue of this integration its transfer price is processor cost. These results are also consistent with Steiner (2004), who cites tough wholesale milk price bargaining by retailers as the reason store brands are procured near processing cost. Moreover the yardstick effect of Stop & Shop integrated processing puts pressure on other retailers to procure store brand milk at or near processing cost.

5 Counterfactual Simulation Analysis

In this section after introducing our simulation technique we describe the counterfactuals explored, provide expectations about equilibrium outcomes, and present the results of our simulations.

5.1 Technique

Given estimates of the structural demand parameters, ownership matrices, response matrices, and market share, one can determine implied channel costs, and equilibrium prices, p_t^*, using the following system of equations that define the market equilibrium:

$$p_t^* = M(T_r, T_w, \triangle_{rt}, \triangle_{wt}, s_t(p_t^*)) + C_t. \tag{11}$$

Where $M(\cdot)$ denotes the implied model for channel margins, $C_t \equiv p_t - M(\ldots, s_t(p_t))$ is channel costs, and p_t are observed prices. Counterfactual equilibria arise under alternative pricing games. We determine the counterfactual equilibrium prices and shares, $s_t(p_t^*)$, by specifying the appropriate counterfactual ownership matrices, T_r and T_w, and response matrices, $\triangle_{rt}$ and $\triangle_{wt}$.

Given equilibrium prices that arise under a particular pricing game the change in consumer surplus, $CS_t(p_t) - CS_t(p_t^*)$, is evaluated using the following formula for the random coefficients logit demand model:

$$CS_{it}(p_t) = \frac{1}{|\alpha_i|}\mathbb{E}\left[max_j V_{ijt}(p_t)\right] = \frac{1}{|\alpha_i|} ln\left(\sum_{j=1}^{J} exp[V_{ijt}(p_t)]\right). \tag{12}$$

In addition to prices, shares, and consumer surplus we compute the difference in channel, retail, and manufacturer profits for each product and for the category within each retailer. This exercise is straight forward given margins implied under factual and counterfactual structures.

5.2 Counterfactual Simulations

The first counterfactual scenario considers the market without Stop & Shop store brand milk, the largest store brand by market share among the four retailers under investigation. This exercise demonstrates the unilateral competitive effects of a strong store brand marketing program. Ex ante one expects Stop & Shop to lose profitability, competing retailers to gain profitability, manufacturers to gain profitability, and consumers to lose welfare. Moreover one expects that competing retailers would increase prices across the category due to less competition. The second counterfactual we evaluate is a market without retail store brands. In this scenario the market reverts to pure manufacturer Stackelberg conduct. With no store brands we expect all retailers to lose profitability, manufacturers to increase profitability, and consumers to lose welfare. Qualitatively the theory under either counterfactual market provides no clear prediction that retail prices on manufacturer brands are higher or lower at retailers that no longer offer a store brand.

Given market structure the answer to the question of equilibrium retail pricing hinges upon consumer demand conditions. For example if a retailer such as Stop & Shop has a particularly strong store brand that is highly substitutable, optimal pricing dictates that they will set higher margins on manufacturer brands and the store brand. Since manufacturers set wholesale price given the retailer's reaction, manufacturers will also set higher margins when Stop & Shop markets a store brand. The dual effect results in higher retail prices for manufacturer brands when Stop & Shop offers a store brand. Conversely if the store brand is less substitutable the retailer does not price manufacturer brands as aggressively. The result is lower margins at both levels of the channel for manufacturers' brands, implying lower retail price. The counterfactual simulations conducted demonstrate the effect.

In addition to revealing the unknown change in equilibrium pricing the counterfactuals demonstrate the relative magnitude of the gains and losses by the winners and the losers in the channel. That is we learn the extent to which double marginalization is overcome. This exercise formally demonstrates the degree to which the effects described by Steiner (2004) and Mills (1995) reallocate welfare in the supply channel.

5.3 Simulation Results

Table 7 reports average percent changes in price, channel profits, retailer profit, manufacturer profit, market share, and consumer surplus for each counterfactual market. Standard errors appear beside each estimate of the mean percentage change.

Results for the no Stop & Shop store brand simulation at the top of table 7 report lower equilibrium prices for the manufacturer brand milks sold in Stop & Shop. This result testifies to the dominant position of Stop & Shop store brand milk. In other retailers prices increase on products across the category as expected. Stop & Shop category profits decline and profits for other retailers and brand manufacturers increase. An additional expected result is that a strong store brand improves your profits in the market by extracting rent both horizontally against competing retailers and vertically against brand manufacturers. Stop & Shop however is not the only loser when it has no store brand. Consumers suffer a decrease in consumer surplus of more than 3% without Stop & Shop store brand availability.

The bottom of table 7 reports impact of the elimination of store brands at all chains. The most interesting finding from this simulation is that Stop & Shop reduces equilibrium retail prices on the manufacturer's brands while the other retails actually increase prices on the same brands. This result signifies that other retailer store brands are not as strong as Stop and Shop's. In other words store brand presence allows the

Stop & Shop to maintain higher margins on manufacturer brands than they otherwise could, in contrast competing retailers otherwise could not. This implies that consumers who regularly purchase manufacturer brand milks from Stop & Shop actually enjoy a boost in surplus if there is no Stop & Shop store brand. The other retailers end up increasing retail prices on the manufacturer's brands. The aggregate impacts of store brands improve milk category profits for all retailers. Under the counterfactual profits generated by store brands flow to brand manufacturers while some are eliminated due to double marginalization in the channel. The net effect negatively impacts consumers who experience a sizeable decrease in surplus of approximately 11.5%.

In sum results from each counterfactual simulation are mostly consistent with what Steiner (2004) describes as a mixed regimen wherein vertical competition between store and manufacturer brands has a net consumer welfare improving effect. Steiner also explains that this regimen is characterized by lower retail prices, lower wholesale prices, and higher retailer profits. We note that this is true under both counterfactuals except for the Stop & Shop retail prices on manufacturer brands. Results also document the extent to which double marginalization is overcome by store brand presence as Mills (1995) suggests.

6 Conclusion

This article empirically explores vertical competition among retailers and manufacturers, horizontal competition at each stage in the channel, and the impact of store brand marketing. Estimating market demand allowed us to use key parameter estimates to conduct supply side analysis by calculating channel profit margins under six alternative channel pricing games. From the estimated channel profit margins we estimate six alternative channel marginal cost models corresponding to each supply channel pricing game. Non-nested tests on the competing models identify the supply model. In it brand manufacturers are Stackelberg channel leaders who exploit retailer reaction functions. Retailers on the other hand take wholesale price as given when maximizing category profits and procure own labeled milk at cost from their own processing plant or an independent manufacturer.

Our analysis of the identification properties of testing non-nested models of channel marginal cost suggest that previous work employing such tests may not be fully identified. In this study chain level data on retailer characteristics enable us to achieve non-parametric identification of the non-nested tests.

In simulations we document that marketing of store brands keeps equilibrium prices lower at most retailers, overcomes double marginalization, and results in higher profits for retailers. Because we assume that channel marginal costs do not change under the counterfactual it is hard to say whether manufacturers benefit by reduction in average costs due to plant utilization efficiencies when processing store brand milk. We also found that if store brands were absent from the market, consumer surplus would decrease by more than 11%.

Going forward in this area of research the availability of wholesale prices or measures of marginal cost would enable formal testing of the identification strategy used for the non-nested hypothesis tests. Also observations of manufacturer marginal costs would determine the extent to which manufacturers benefit from the plant utilization efficiencies of store brand production. Each of these questions remain as interesting avenues that could be explored in the future, if such data become available for public research.

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Table 1: Market Shares, Within Retailer Share, Prices: Summary Statistics

Retailer		Manufacturer	Mean	S.D.	Minimum	Maximum
Market Share	*Chain Share*					
Stop&Shop	0.180	Hood	0.022	0.005	0.013	0.029
		Garelick	0.032	0.003	0.026	0.038
		Store Brand	0.126	0.006	0.112	0.140
Shaws	0.137	Hood	0.009	0.007	0.000	0.017
		Garelick	0.030	0.006	0.017	0.040
		Store Brand	0.097	0.011	0.073	0.117
Demoulas	0.123	Hood	0.006	0.002	0.003	0.011
		Garelick	0.007	0.003	0.003	0.011
		Store Brand	0.111	0.010	0.090	0.131
Star	0.082	Hood	0.013	0.003	0.008	0.018
		Garelick	0.026	0.003	0.017	0.032
		Store Brand	0.043	0.007	0.029	0.053
Group Share						
Stop&Shop	0.180	Hood	0.121	0.023	0.076	0.159
		Garelick	0.180	0.017	0.147	0.227
		Store Brand	0.699	0.017	0.661	0.746
Shaws	0.137	Hood	0.070	0.052	0.000	0.134
		Garelick	0.221	0.030	0.164	0.274
		Store Brand	0.709	0.037	0.633	0.764
Demoulas	0.123	Hood	0.048	0.022	0.024	0.094
		Garelick	0.053	0.025	0.025	0.093
		Store Brand	0.898	0.045	0.832	0.949
Star	0.082	Hood	0.162	0.043	0.099	0.236
		Garelick	0.316	0.018	0.279	0.356
		Store Brand	0.523	0.044	0.448	0.604
Price per gallon						
Stop&Shop	0.180	Hood	$2.772	$0.113	$2.460	$2.961
		Garelick	$2.731	$0.207	$2.363	$3.072
		Store Brand	$2.436	$0.117	$2.251	$2.685
Shaws	0.137	Hood	$2.765	$0.151	$2.408	$3.087
		Garelick	$2.708	$0.181	$2.426	$3.058
		Store Brand	$2.395	$0.126	$2.207	$2.651
Demoulas	0.123	Hood	$2.776	$0.077	$2.597	$2.924
		Garelick	$2.646	$0.135	$2.380	$2.935
		Store Brand	$2.211	$0.101	$2.054	$2.411
Star	0.082	Hood	$2.925	$0.091	$2.761	$3.143
		Garelick	$2.786	$0.156	$2.567	$3.168
		Store Brand	$2.434	$0.134	$2.236	$2.723

Source: IRI

Table 2: Promotion, Package Size, Skim to Whole Ratio: Summary Statistics

Retailer	Manufacturer	Mean	Median	S.D.	Minimum	Maximum
Weighted Price Reduction						
Stop&Shop	Hood	8.33	7.78	5.30	0	22.89
	Garelick	8.99	7.48	6.59	0	27.37
	Store Brand	8.29	8.30	3.19	0	16.68
Shaws	Hood	7.42	8.29	7.17	0	26.83
	Garelick	11.48	12.18	5.54	0	24.89
	Store Brand	8.04	8.50	4.34	0	19.22
Demoulas	Hood	1.86	0.00	3.00	0	7.00
	Garelick	2.08	0.00	3.16	0	11.16
	Store Brand	4.17	4.94	3.74	0	11.95
Star	Hood	7.65	7.32	4.16	0	17.03
	Garelick	9.41	9.47	4.51	0	21.05
	Store Brand	5.50	5.93	3.23	0	12.75
Units per Volume						
Stop&Shop	Hood	0.187	0.186	0.009	0.175	0.227
	Garelick	0.187	0.186	0.006	0.175	0.213
	Store Brand	0.171	0.172	0.004	0.157	0.178
Shaws	Hood	0.199	0.199	0.005	0.185	0.209
	Garelick	0.158	0.158	0.002	0.154	0.163
	Store Brand	0.277	0.264	0.026	0.239	0.318
Demoulas	Hood	0.236	0.239	0.018	0.192	0.278
	Garelick	0.154	0.157	0.005	0.147	0.162
	Store Brand	0.288	0.292	0.013	0.265	0.306
Star	Hood	0.201	0.201	0.006	0.185	0.214
	Garelick	0.165	0.166	0.002	0.160	0.172
	Store Brand	0.270	0.265	0.015	0.247	0.295
Skim to Whole Ratio						
Stop&Shop	Hood	12.52	12.16	1.85	7.69	17.92
	Garelick	16.53	16.31	2.13	11.11	22.08
	Store Brand	10.73	10.75	0.33	9.99	11.61
Shaws	Hood	7.17	8.66	3.22	1.06	10.69
	Garelick	14.32	14.23	2.04	11.35	18.45
	Store Brand	11.57	11.47	0.70	10.25	12.73
Demoulas	Hood	4.20	4.20	1.29	2.10	6.28
	Garelick	4.19	4.07	0.83	2.96	7.46
	Store Brand	12.47	12.43	0.38	11.80	13.54
Star	Hood	8.53	8.93	2.39	4.94	14.41
	Garelick	14.13	13.77	2.16	10.45	20.73
	Store Brand	11.56	11.73	0.81	9.16	14.23

Source: IRI

Table 3: Income, Services, Cost Proxies and Input Costs: Summary Statistics

Retailer	Variable	Mean	Median	S.D.	Minimum	Maximum
	Income	$18,003	$17,894	$1,398	$16,240	$19,787
Stop&Shop	Number of stores	69.65	70.5	4.40	61	74
	Bakery	0.861	0.888	0.056	0.730	0.904
	Bank	0.578	0.605	0.053	0.453	0.622
	Restaurant	0.043	0.054	0.017	0.015	0.057
	Pharmacy	0.567	0.599	0.075	0.423	0.649
	Seafood Counter	0.947	0.957	0.032	0.880	0.990
	Volume Sales	491559	509857	41520	426689	553425
	Retial Sq Footage	41178	42234	3293	33932	44730
Shaws	Number of stores	46.45	46	1.61	43	49
	Bakery	0.924	1	0.123	0.708	1
	Bank	0.391	0.391	0.059	0.313	0.486
	Restaurant	0.064	0.066	0.048	0	0.136
	Pharmacy	0.055	0.043	0.026	0.019	0.093
	Seafood Counter	1	1	0	1	1
	Volume Sales	35388	36149	2528	30125	38111
	Retial Sq Footage	24991	24903	355	24465	25558
Demoulas	Number of stores	32.1	32	0.31	32	33
	Bakery	0.544	0.588	0.093	0.352	0.633
	Bank	0.046	0.000	0.064	0.000	0.156
	Restaurant	0.055	0.062	0.013	0.031	0.063
	Pharmacy	0.017	0.000	0.028	0.000	0.063
	Seafood Counter	0.829	0.882	0.102	0.641	0.917
	Volume Sales	555204	566927	32652	497656	598438
	Retial Sq Footage	38641	40026	5496	27087	44781
Star	Number of stores	39.25	39.5	2.75	33	42
	Bakery	0.978	1	0.032	0.920	1
	Bank	0.365	0.383	0.059	0.244	0.429
	Restaurant	0.180	0.173	0.078	0.095	0.360
	Pharmacy	0.370	0.382	0.047	0.273	0.424
	Seafood Counter	0.971	0.970	0.019	0.945	1
	Volume Sales	405614	419367	35431	327000	435888
	Retial Sq Footage	35260	34617	2756	32196	41819
	Costs					
	Price of raw Milk	$1.40	$1.39	$0.10	$1.23	$1.66
	Electric	$7.67	$7.86	$0.93	$5.19	$9.27
	Diesel	$112.42	$113.21	$12.23	$89.33	$131.72

Source: Income: Market Scope, Retailer Characteristics: Spectra Marketing,
Costs: Federal Milk Market Order and Energy Information Association

Table 4: Demand Model Parameter Estimates

Characteristic	Standard Logit Coefficient	Standard Logit s.e.	Random Coefficient Logit Coefficient	Random Coefficient Logit s.e.	RC s.d.	s.e.
Price	-49.6700	8.9106	-45.5935	3.5694	0.2567	0.3673
weighted price reduction	0.0102	0.0061	0.0128	0.0414	0.0136	0.2203
units per volume	6.0518	1.6961	6.4223	0.4093	0.1523	0.0512
skim to whole ratio	0.1223	0.0111	0.1372	0.1357	0.0036	1.6531
income	0.0003	0.6059	4.9131	0.9217	0.0053	2.7163
constant	-2.4146	1.2676	-2.8265	0.3004	0.0477	0.1635
Food Service						
Hood	6.0198	0.9764	5.3733	0.6654	0.9186	0.4492
Garelick	3.1616	1.0100	-10.2062	1.7682	14.4288	2.2011
Store Brand	-5.3026	0.9808	-11.3609	4.0058	9.7955	0.5535
Non-Food Service						
Hood	2.9124	0.4200	2.5326	2.4308	0.6876	0.1569
Garelick	0.2042	0.4862	0.1406	0.3262	0.4150	0.3120
Store Brand	4.2996	0.6844	4.5662	0.0647	0.4241	1.0919
		p-value		p-value		
Centered R^2	0.8684		0.8648			
Hansen J	1.7725	0.8796	3.6341	0.6032		
F-Statistic	279.9261	0.0000	128.2680	0.0000		
No. Overidentifying Restrictions	5		8			
Market size - servings	Sensitivity of Estimated Price Coefficient to market Definition					
4 oz	-53.6048	9.2005	-47.3111	3.6856	0.1000	0.0105
6 oz	-49.6700	8.9106	-45.5935	3.5694	0.2567	0.3673
8 oz	-47.5666	8.8204	-43.1808	3.5333	0.0335	0.0105

Note: Regressions include brand dummies and and quarter dummies. RC s.d is the estimate of the standard deviation of the random coefficient

Table 5: Mean Demand Elasticity Estimates

	4oz serving		8oz serving		6oz serving											
	own	ave cross	own	ave cross	SS Hood	SS Gar	SS SB	D Hood	D Gar	D SB	Sh Hood	Sh Gar	Sh SB	St Hood	St Gar	ST SB
SS Hood	-8.166	0.038	-7.462	0.026	-7.870	0.067	1.178	0.080	0.205	0.424	0.130	0.177	0.364	0.226	0.343	0.843
SS Gar	-7.746	0.072	-7.085	0.050	0.035	-7.467	1.166	0.079	0.217	0.422	0.128	0.195	0.364	0.221	0.361	0.835
SS SB	-5.108	1.338	-4.972	0.889	0.034	0.064	-5.068	0.076	0.197	0.447	0.123	0.166	0.390	0.215	0.330	0.889
D Hood	-8.081	0.084	-7.390	0.058	0.036	0.067	1.178	-7.791	0.207	0.425	0.132	0.177	0.363	0.228	0.343	0.845
D Gar	-7.649	0.259	-7.011	0.179	0.032	0.066	1.070	0.071	-7.360	0.408	0.115	0.527	0.353	0.203	0.424	0.772
D SB	-6.472	0.506	-6.029	0.347	0.031	0.059	1.136	0.068	0.191	-6.284	0.111	0.159	0.629	0.202	0.316	0.946
Sh Hood	-8.497	0.136	-7.778	0.094	0.036	0.067	1.175	0.081	0.205	0.427	-8.193	0.176	0.368	0.233	0.344	0.847
Sh Gar	-6.981	0.250	-6.165	0.171	0.026	0.056	0.860	0.055	0.431	0.338	0.087	-6.371	0.293	0.166	0.478	0.617
Sh SB	-5.814	0.455	-5.559	0.302	0.026	0.051	1.005	0.056	0.173	0.590	0.092	0.142	-5.849	0.180	0.290	0.966
St Hood	-7.926	0.244	-7.289	0.167	0.036	0.067	1.171	0.080	0.204	0.431	0.133	0.171	0.379	-7.654	0.342	0.854
St Gar	-7.604	0.405	-7.027	0.280	0.034	0.068	1.120	0.075	0.267	0.416	0.122	0.328	0.365	0.213	-7.367	0.808
St SB	-6.117	0.996	-5.736	0.649	0.032	0.061	1.180	0.072	0.192	0.482	0.117	0.160	0.489	0.209	0.321	-5.993

Note: Cell i,j, where i indexes row and j indexes columns, gives the percent change in market share for brand i for a one percent change in the price of brand j

Note: Stop & Shop, Demoulas, Shaws, and Star Market are indicated by SS, D, Sh, and St respectively.

Source: Author's calculations

Table 6: Smith Test for Competing Non-nested Models of Channel Cost: 1000 Bootstrap Replications

Smith Test Statistic: $Plim_2\{\frac{1}{\omega\sqrt{n}}[J_1(\theta_1) - J_2(\theta_2)]\} \rightarrow N(0,1)$

			H_2		
H_1	**Model 2**	Model 3	Model 4	Model 5	Model 6
Model 1	**-4.35**	-2.69	-2.42	1.01	-6.26
	0.00	0.00	0.01	0.84	0.00
Model 2		**5.16**	**0.47**	**-0.13**	**3.27**
		1.00	**0.68**	**0.45**	**1.00**
Model 3			-1.37	-0.70	9.84
			0.09	0.24	1.00
Model 4				0.68	0.47
				0.75	0.68
Model 5					-1.73
					0.84

Note: lower tail p-values appear below statistic values

Table 7: Simulation Results

	% Change in Price		% Change in Channel Profits		% Change in Retail Profits		% Change in Manufacturer Profits		% Change in Market Share	
	mean	s.e.	mean	s.e.	mean	s.e.	mean	s.e.	mean	s.e.
Market without Stop & Shop Store Brand										
SS Hood	-0.023	0.0011	7.610	2.377	6.500	2.077	8.960	2.749	8.326	2.568
SS Gar	-0.020	0.0014	5.500	1.894	4.678	1.648	6.434	2.183	5.960	2.036
% Change in SS Category Profit			-0.186	0.094	-0.445	0.055	1.691	0.761		
D Hood	0.009	0.0009	4.511	1.301	4.544	1.308	4.475	1.294	4.336	1.262
D Gar	0.012	0.0010	2.829	0.918	2.805	0.910	2.849	0.925	2.688	0.884
D SB	0.006	0.0006	0.910	0.360	0.910	0.360			0.850	0.351
% Change in D Category Profit			0.135	0.117	0.082	0.104	0.995	0.465		
Sh Hood	0.008	0.0008	1.971	0.656	1.961	0.652	1.981	0.660	1.878	0.632
Sh Gar	0.013	0.0012	1.780	0.712	1.752	0.706	1.803	0.716	1.700	0.695
Sh SB	0.007	0.0005	2.478	0.702	2.478	0.702			2.369	0.682
% Change in Sh Category Profit			0.198	0.117	0.167	0.113	0.603	0.255		
St Hood	0.015	0.0015	1.648	0.617	1.714	0.628	1.572	0.606	1.542	0.597
St Gar	0.017	0.0014	1.878	0.489	1.966	0.507	1.789	0.471	1.724	0.460
St SB	0.016	0.0015	1.767	0.779	1.767	0.779			1.478	0.661
% Change in St Category Profit			0.215	0.158	0.210	0.158	0.650	0.263		
								% Change in Consumer Surplus	-3.089	1.271
Market without Retail Store Brands										
SS Hood	-0.010	0.002	6.747	3.004	5.829	2.699	7.831	3.366	7.148	3.207
SS Gar	-0.002	0.003	7.240	2.565	6.268	2.304	8.300	2.843	7.568	2.675
% Change in Category Profit			-0.202	0.105	-0.469	0.065	1.605	0.686		
D Hood	0.014	0.003	2.265	0.765	2.105	0.742	2.426	0.788	2.191	0.764
D Gar	0.028	0.005	2.844	0.801	2.436	0.698	3.199	0.894	2.521	0.729
% Change in Category Profit			-0.171	0.080	-0.400	0.059	1.011	0.486		
Sh Hood	0.015	0.003	1.497	0.597	1.260	0.516	1.732	0.680	1.279	0.515
Sh Gar	0.026	0.004	0.692	0.214	0.552	0.198	0.810	0.229	0.594	0.204
% Change in Category Profit			-0.192	0.073	-0.394	0.053	0.388	0.176		
St Hood	0.017	0.005	1.105	0.337	0.918	0.306	1.318	0.372	1.010	0.333
St Gar	0.029	0.006	1.461	0.437	1.190	0.386	1.733	0.486	1.223	0.368
% Change in Category Profit			-0.261	0.058	-0.465	0.039	0.599	0.219		
								% Change in Consumer Surplus	-11.559	4.673

Source: Author's Calculations