Appendix for: Competitive Price Discrimination Strategies in a Vertical Channel Using Aggregate Retail Data

David Besanko[1] Jean-Pierre Dubé[2] Sachin Gupta[3]

July 2002

[1]Kellogg School of Management, Northwestern University, d-besanko@nwu.edu.
[2]Graduate School of Business, University of Chicago, jdube@gsb.uchicago.edu.
[3]Johnson Graduate School of Management, Cornell University, sg248@cornell.edu

1 Appendix A: Model Estimation with Simulated Aggregate Data

In this section, we demonstrate via numerical simulations that the econometric model described in Sections 2 and 3 can recover the structure of the underlying segments from aggregate store-level data. The primary objective of our analysis is to show the performance of the model for realistic marketing data.

Table 1 describes the parameters of the simulated market. The market consists of five segments labeled A through E. Within each segment, consumers are identical and make logit choices across six brands, each produced by a separate firm, and a no-purchase alternative. The impact of all fixed product attributes and brand reputations is captured by brand-specific constants, which differ across segments. Prices affect utilities and hence choices, and are assumed to be exogenous. Prices of the six brands are generated from independent Uniform distributions. Since the objective here is to show recoverability of demand heterogeneity, we do not deal with issues of price endogeneity.

We assume that data are pooled across 50 stores and two years (100 weeks). These appear to be reasonable choices for a medium to large sized supermarket chain. We generate store-trips at the individual level, and the choice parameters and prices given above result in discrete choices from the set of six products and no-purchase. These are aggregated to obtain weekly brand shares. In Table 2 we show the average brand shares of the total number of store visits.

1.1 Estimation Results

The baseline demand model described in Sections 2 and 3 is estimated using GMM. In evaluating the quality of model estimates we focus on two metrics that are relevant for the pricing application: price elasticities, and estimated equilibrium margins. These are considered both for the aggregate market, and separately for each segment. We use absolute percentage deviation as the measure of bias. It is relevant to note that this measure includes both bias and variance, since only one sample was used for the estimation. Ideally we would use several replicates of simulated samples, which would allow us to separate bias from variance. However, the computational cost of conducting such an analysis for multiple samples is prohibitive.

In Table 3, we report the estimated aggregate price elasticities and the percentage absolute deviation from the true elasticities. The mean absolute percentage deviation in own elasticities in Table 3 is 2.7%, while the mean absolute percentage deviation in cross elasticities is 12.4%. Thus, the aggregate elasticities are recovered quite well by the model.

In Table 4 we provide the estimated own and cross price elasticities for each of the five segments, and the mean absolute percentage deviation from true elasticities. Note that cross-price elasticities are restricted within segments because of the IIA property of the logit model.

With the exception of segment 1, the smallest segment, the own price elasticities are estimated with relatively small deviation. While the percentage deviation in cross elasticities is larger, the absolute values of the cross elasticities to which these apply are quite small.

In Table 5 we compare true with estimated equlibrium margins for each segment and for the aggregate market. Absolute percentage deviation is in parentheses. The results indicate that the estimated margins are very close to the true margins in aggregate and for each segment, with the exception of segment 1.

2 Appendix B: Alternative Model Specifications

We now derive two comparison models for our baseline Manufacturer Stackelberg (MS) model. The first comparison model, the Vertical Nash (VN) equilibrium, focuses on an alternative channel game. In the VN game, retailers and manufacturers move simultaneously and it is conjectured that the retail pass-through rate of wholesale prices is exactly equal to one. The advantage of this particular game structure is that the resulting equilibrium price conditions are much simpler than those of the MS, giving it a practical advantage over MS.

The second comparison model, the nested logit, focuses on more a modified specification of consumer preferences. By adding a nest structure in which consumers first pick whether or not to purchase and then which brand to purchase, we effectively relax the condition that consumers switch between inside and outside goods in the same manner. The channel model here is MS.

2.1 Vertical Nash Model (VN)

In the VN model (Choi 1991 and Besanko, Gupta and Jain 1998), oligopolistic manufacturers set wholesale prices and sell through a monopoly retailer. The key elements of the model are as follows:

1. The retailer acts as a monopolist in its local area. This assumption is broadly consistent with retailer conventional wisdom that most consumers shop at the same store week after week, often the one closest to their home or workplace (Slade, 1995). BGJ (1998) provide further support for this assumption. The size of this local market is M.

2. The retailer cannot price discriminate across the K segments.

3. There are N manufacturers, with a typical manufacturer denoted by n. Each manufacturer offers a set B_n of brands, with $\cup_{n=1}^{N} B_n = J$.

4. Consumers act as utility-maximizing price-takers, as described in Section 2. The game between manufacturers and the retail chain unfolds as follows:

   (a) The manufacturers and the retailer move simultaneously.

   (b) Each manufacturer n takes retail margins and the wholesale prices of other manufacturers as given, and chooses its set of wholesale prices, $\{w_j,\ j \in B_n\}$, to maximize its product-line profits.

   (c) The retailer takes wholesale prices as given, and chooses the set of retail prices $\{p_j,\ j \in J\}$ to maximize its overall category profits.

The profit-maximization problem of manufacturer n is:

$$\max_{\{w_i, i \in B_n\}} \Pi_n = \sum_{i \in B_n} (w_i - mc_i) X_i,$$

where mc_i is the manufacturer's marginal cost for brand i and $X_i = S_i M$ is the demand for brand i. Using the random coefficients demand model as described in the paper, the first-order condition for a typical brand j is:

$$\sum_{i=1}^{J} (w_i - mc_i) \Upsilon_{ji} \left(\sum_{k=1}^{K} \lambda^k \frac{\partial S_i^k}{\partial p_j} M \right) + \sum_{k=1}^{K} \lambda^k S_j^k M = 0,$$

where

$$\Upsilon_{ji} = \begin{cases} 1 \text{ if brands } j \text{ and } i \text{ are offered by the same manufacturer.} \\ 0 \text{ if brands } j \text{ and } i \text{ are offered by different manufacturers.} \end{cases}$$

Noting that

$$\frac{\partial S_j^k}{\partial p_j} = -\alpha^k S_j^k (1 - S_j^k), \tag{1}$$

$$\frac{\partial S_i^k}{\partial p_j} = \alpha^k S_i^k S_j^k \tag{2}$$

the system of first-order conditions for brands $1, \ldots, J$ can be written in matrix form as:

$$\mathbf{\Phi}(\mathbf{w} - \mathbf{mc}) + \mathbf{v} = \mathbf{0}, \tag{3}$$

where

$$\mathbf{w} - \mathbf{mc} \equiv \begin{bmatrix} w_1 - mc_1 \\ \vdots \\ w_J - mc_J \end{bmatrix}_{J \times 1}$$

$$\mathbf{\Phi} \equiv \begin{bmatrix} -\Upsilon_{11} \left(\sum_{k=1}^{K} \lambda^k \alpha^k S_1^k (1 - S_1^k) M \right) & \cdots & \Upsilon_{1J} \left(\sum_{k=1}^{K} \lambda^k \alpha^k S_1^k S_J^k M \right) \\ \vdots & \ddots & \vdots \\ \Upsilon_{J1} \left(\sum_{k=1}^{K} \lambda^k \alpha^k S_J^k S_1^k M \right) & \cdots & -\Upsilon_{JJ} \left(\sum_{k=1}^{K} \lambda^k \alpha^k S_J^k (1 - S_J^k) \lambda^k M \right) \end{bmatrix}_{J \times J}$$

$$\mathbf{v} = \begin{bmatrix} \sum_{k=1}^{K} \lambda^k S_1^k M \\ \vdots \\ \sum_{k=1}^{K} \lambda^k S_J^k M \end{bmatrix}_{J \times 1}.$$

This represents a system of J equations, one for each brand.

The retailer takes the wholesale prices as given, and acts a monopolist in pricing the whole category. The retailer's problem is thus:

$$\max_{p_1, \ldots, p_J} \Pi_R = \sum_{i=1}^{J} (p_i - w_i) X_i. \tag{4}$$

The first-order condition for a typical brand j is:

$$\sum_{i=1}^{J}(p_i - w_i)\left(\sum_{k=1}^{K}\lambda^k \frac{\partial S_i^k}{\partial p_j}M\right) + \sum_{k=1}^{K}\lambda^k S_j^k M = 0.$$

Using (1) and (2), the retailer's system of first-order conditions can be written in matrix form as:

$$(\mathbf{p} - \mathbf{w}) + \mathbf{v} = \mathbf{0}, \tag{5}$$

where:

$$\mathbf{p} - \mathbf{w} \equiv \begin{bmatrix} p_1 - w_1 \\ \vdots \\ p_J - w_J \end{bmatrix}_{J\times 1},$$

and

$$\equiv \begin{bmatrix} -\sum_{k=1}^{K}\lambda^k\alpha^k S_1^k(1-S_1^k)M & \cdots & \sum_{k=1}^{K}\lambda^k\alpha^k S_1^k S_J^k M \\ \vdots & \ddots & \vdots \\ \sum_{k=1}^{K}\lambda^k\alpha^k S_J^k S_1^k M & \cdots & -\sum_{k=1}^{K}\lambda^k\alpha^k S_J^k(1-S_J^k)M \end{bmatrix}_{J\times J}.$$

Summarizing the full vertical equilibrium, the retailer's profit-maximization conditions in (5)constitute J equations, while the manufacturer's first-order conditions in (3) constitute J equations. Thus, the supply side of the model entails $2J$ conditions. The demand side of the model consists of KJ equations: for each of the segments there is one demand equation for each of the J brands, which we can express in log form as:

$$\begin{aligned} \ln S_j^k &= \ln(1 - \sum_{i=1}^{J} S_i^k) + x_j\beta^k - \alpha^k p_j + \xi_j, \\ k &= 1, ..., K, j = 1, \ldots, J. \end{aligned}$$

Thus, in total, we have $(K+2)J$ equations. Similarly, there are $(K+2)J$ unknowns:

- J wholesale prices: $w_1, \ldots w_J$
- J retail prices: $p_1, \ldots, p_J$.
- KJ market shares: $(S_1^1, \ldots, S_J^1), \ldots, (S_1^K, \ldots, S_J^K)$.

2.2 Nested Logit Model of Demand

The nested logit model is very similar in form to the baseline random coefficients model of demand. Technically, we add an additional error component to the utility function to allow for correlation between the utilities of the inside goods. Following the approach of Cardell (1996) (see also Berry 1994), one can interpret the nested logit model as a special case of random coefficients. First, we group all the alternatives into two groups, the brands in the category, and no-purchase. Ignoring time-subscripts, the utility a household h derives from a given alternative has the following form:

$$\begin{aligned} u_{hj} &= x_j\beta_h - \alpha_h p_j + \xi_j + \zeta_{purch} + (1-\sigma)\,\omega_{hj}, j = 1, ..., J \\ u_{hj} &= \zeta_0 + (1-\sigma)\,\omega_{hj}, j = 0. \end{aligned}$$

The new feature of the utility function is the inclusion of the error components ζ_{purch} to all of the brands and ζ_0 to the no-purchase alternative. The random variable ζ has a distribution dependent on the $\sigma \in [0,1]$. To make the link to the standard nested logit specification, Cardell (1997) shows that the distribution of ζ is defined such that $\zeta + (1-\sigma)\,\omega$ has an extreme value distribution. Berry (1994) shows that one can think of this formulation as a random coefficients model in which random parameters ζ are assigned to group dummy variables. In the current context, we effectively specify random coefficients on the dummy variable for purchase versus no-purchase, $I_{purch} = \begin{cases} 1, \text{if purch} \\ 0, else \end{cases}$:

$$\begin{aligned} u_{hj} &= x_j\beta_h - \alpha_h p_j + \xi_j + \zeta_{purch} I_{purch} + (1-\sigma)\,\omega_{hj}, j = 1, ..., J \\ u_{hj} &= \zeta_0(1 - I_{purch}) + (1-\sigma)\,\omega_{hj}, j = 0. \end{aligned}$$

Conditional on purchase, it is well-known that the corresponding within-purchase-group market shares are:

$$\widetilde{S_j^k} = \frac{\exp(\frac{x_j\beta^k - \alpha^k p_j + \xi_j}{1-\sigma})}{G_{purch}}$$

where $G_{purch} = \sum_{i=1}^{J} \exp(\frac{x_i\beta^k - \alpha^k p_i + \xi_i}{1-\sigma})$ is the exponent of the "inclusive value" for the brands. The corresponding purchase incidence probability is thus:

$$S_{purch}^k = \frac{G_{purch}^{(1-\sigma)}}{1 + G_{purch}^{(1-\sigma)}}.$$

Finally, the corresponding unconditional market share for a brand j is:

$$S_j^k = \widetilde{S_j^k} S_{purch}^k = \frac{\exp(\frac{x_j\beta^k - \alpha^k p_j + \xi_j}{1-\sigma})}{G_{purch}^{\sigma}\left[1 + G_{purch}^{(1-\sigma)}\right]}, j = 1, ..., J$$

Since the baseline demand specification already has random coefficients on the brand intercepts (implicit in $x_j\beta_h$ is a matrix of household-specific brand dummy variables) we have already controlled for heterogeneity across consumers' valuation of purchase versus non-purchase alternatives. However, by including the nested logit term, we allow for the distribution of tastes for purchase versus non-purchase alternatives to differ. This difference can be seen, for instance, in the computation of marginal price effects (and thus margins in corresponding MS model):

$$\frac{\partial S_j^k}{\partial p_j} = \frac{\alpha^k S_j^k}{1-\sigma}(1 - \sigma S_j^k \widetilde{S_j^k} - (1-\sigma)\,S_j^k), j = 1, ..., J \tag{7}$$

$$\frac{\partial S_i^k}{\partial p_j} = \begin{cases} -\frac{\alpha^k S_i^k}{1-\sigma}\left(S_j^k + \sigma\widetilde{S_j^k}\right), i, j = 1, ..., J \\ -\alpha^k S_0^k S_j^k, i = 0 \end{cases}. \tag{8}$$

Unlike the baseline demand model, the cross-price elasticities amongst brands are inherently different from those with respect to the no-purchase alternative. Margins are obtained by substituting the share derivatives with respect to prices into the first-order conditions of the retailer and manufacturers as derived in the paper.

2.3 Empirical Results for Comparison Models

We now report the empirical findings from our baseline model, the Manufacturer Stackelberg model with random coefficients demand and results for the two comparison models, the Vertical Nash model with random coefficients demand and the Manufacturer Stackelberg model with random coefficients and nested logit demand. To simplify the presentation, we first present the demand parameters in tables 6, 7 and 8. We then present the corresponding marginal cost function parameters and the median marginal cost per oz for each of the products, across the store weeks in the data, in tables 9, 10 and 11.

2.3.1 Model Comparisons on Predictive Fit

To assess predictive fit of the three models, we report out-of-sample root mean-square errors in Table 12. Each of the models is re-estimated using only the first 92 weeks. The remaining 10 weeks are used for hold-out prediction. In the 10-week holdout sample, we compute the equilibrium prices and shares for each store-week (using the econometric error for the unobserved attribute values). We then compute the root mean square error between observed and predicted equilibrium prices and shares. Interestingly, we find that each of the models seems to perform equally well in terms of prices. In terms of shares, there appears to be a slight performance improvement using our baseline MS model. These results are not so surprising. In comparison with the VN model, the pricing equations for the proposed MS model are very similar. If demand parameters were identical, both models would predict the same retail margins. The only difference is thus the wholesale prices and the marginal costs. Since wholesale prices are imputed from the channel game assumption, the distinction between the two models lies entirely in the marginal cost estimates. Since we do not have any firm-specific cost-related information, it will be difficult to perform an accurate test to compare the MS and VN model specifications.

Comparing the proposed model with the nested logit model, since the estimated nesting parameter, σ, is very small, there is very little implied correlation in the within-nest utilities. As a result, the MS and nested logit MS are indeed quite similar. This outcome is also not very surprising since we already account for correlation in the utilities by estimating correlated random brand intercepts. Furthermore, we allow the outside good probability to vary by store. As a result, the nesting parameter is only picking up the fact that the distribution of the error for the outside good is different from that of the inside goods.

2.3.2 Model Comparisons on Implied Margins and Estimated Marginal Costs

Since our out-of-sample predictions do not provide a clear dominance of one model, we also compare the models based on implied margin estimates and on estimated marginal costs. Note that the proposed MS model results in non-negative marginal cost estimates for each product, which is intuitive, while the two benchmark models lead to one or more negative marginal cost estimates. We show in table 13 retailer margins estimated according to the three models, computed as a percentage of the actual retail price in the data, for each of the products as well as the category average. Note that the proposed Manufacturer Stackelberg model estimates the lowest retail margins among the three models, and margins estimated by the Vertical Nash model are by far the highest. We attempted to obtain data on retailer or wholesaler margins in order to assess the external validity of the estimated margins. Unfortunately information on margins was unavailable for the time period (1986-88) of our data. We were able to obtain retailer margins for ketchup products for recent years from one major US supermarket chain. (This firm wishes to remain unidentified.) However, three of the four products are no longer available in their original pack sizes or forms (the squeezable plastic bottle is the dominant pack form now, unlike the glass bottle at the time of the data). Consequently product-level comparisons are not possible. The (simple) average percentage retail margin for ketchup for this retailer is 34.5% for years 2001 and 2002. This number comes closest to the estimated average margin from the proposed model (39.5%). More importantly, this evidence questions the validity of the high margins estimated by the Vertical Nash model.

References

[1] Berry, S. [1994], "Estimating Discrete-Choice Models of Product Differentiation," *Rand Journal of Economics,* 25, 242-62.

[2] Besanko, D., S. Gupta and D. Jain [1998], "Logit Demand Estimation Under Competitive Pricing Behavior: An Equilibrium Framework," *Management Science*, November.

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

[4] Chintagunta, P. [2002], "Investigating Category Pricing Behavior at a Retail Chain." *Journal of Marketing Research*, 39, May, 141-154.

[5] Choi, S. Chan [1991], "Price Competition in a Channel Structure with a Common Retailer" *Marketing Science*, 10, 271-296.

[6] Cotterill, R.W. and W.P. Putsis [2001], "Do Models of Vertical Strategic Interaction for National and Store Brands Meet the Market Test?" *Journal of Retailing*, 77, 83-109.

[7] Draganska, M. and D.C.Jain [2001], "Product Line Length and Competitive Pricing: An Empirical Study," working paper, Stanford University.

[8] Slade, M.E. [1995], "Product Market Rivalry with Multiple Strategic Weapons: an analysis of price and advertising competition," *Journal of Economics and Management Strategy*, 4, 445-476.

[9] Sudhir, K. [2001b], “Structural Analysis of Competitive Pricing in the Presence of a Strategic Retailer.” *Marketing Science*, 20, 244-64.

[10] M. Villas-Boas and Ying Zhao [2001], ”The Ketchup Marketplace: Retailer, Manufacturers, and Individual Consumers,” working paper, University of California at Berkeley.

Parameter	*Segment A*	*Segment B*	*Segment C*	*Segment D*	*Segment E*
Brand constant 1	1	-0.2	-1.0	0.8	0.5
Brand constant 2	0.5	0.8	0.2	0.5	0.8
Brand constant 3	0	-1.0	1.2	-0.4	1.0
Brand constant 4	-0.5	-0.6	-1.0	1.6	-0.5
Brand constant 5	-0.8	-0.4	-1.2	-1.0	1.5
Brand constant 6	-1	-0.2	-0.6	-0.4	-1.0
Price-response coefficient	1.5	2.0	3.0	4.0	5.0
Segment proportions	0.10	0.15	0.20	0.25	0.30

Table 1: Demand Parameters for Simulated Market

Brand	Share
1	10.4%
2	13.3%
3	12.4%
4	10.0%
5	8.4%
6	4.3%
No Purchase	41.2%

Table 2: Shares in Simulated Market

Change in Price	Change in Purchase Probability					
	Brand 1	Brand 2	Brand 3	Brand 4	Brand 5	Brand 6
Brand 1	-1.35 (1)	0.23 (21)	0.15 (10)	0.17 (16)	0.13 (4)	0.04 (25)
Brand 2	0.18 (17)	-1.35 (2)	0.16 (8)	0.14 (4)	0.16 (16)	0.06 (20)
Brand 3	0.12 (6)	0.18 (9)	-1.38 (0)	0.08 (11)	0.16 (3)	0.06 (1)
Brand 4	0.17 (20)	0.18 (6)	0.10 (12)	-1.27 (11)	0.06 (24)	0.08 (11)
Brand 5	0.16 (1)	0.26 (16)	0.24 (4)	0.07 (23)	-1.75 (0)	0.05 (13)
Brand 6	0.11 (22)	0.18 (15)	0.20 (9)	0.20 (20)	0.09 (7)	-1.37 (2)

Table 3: Estimated Aggregate Price Elasticities and (Percentage Absolute Deviation from True Elasticities)

segment	elasticity	Brand 1	Brand 2	Brand 3	Brand 4	Brand 5	Brand 6	Average % Deviation
A	Own	-0.88	-0.86	-1.03	-1.05	-1.04	-1.08	52.13
	Cross	0.23	0.25	0.08	0.06	0.07	0.03	30.26
B	Own	-1.02	-0.85	-0.97	-0.98	-0.94	-0.85	7.66
	Cross	0.01	0.18	0.06	0.06	0.09	0.18	46.89
C	Own	-1.63	-1.61	-1.09	-1.65	-1.64	-1.63	13.41
	Cross	0.08	0.10	0.62	0.05	0.06	0.08	29.95
D	Own	-1.91	-1.92	-2.03	-1.23	-2.06	-2.00	7.28
	Cross	0.18	0.17	0.06	0.86	0.03	0.09	26.68
E	Own	-2.47	-2.34	-2.36	-2.60	-2.12	-2.62	5.37
	Cross	0.17	0.30	0.28	0.04	0.52	0.02	19.87

Table 4: Estimated Segment-level Own and Cross Price Elasticities and Average Percentage Absolute Deviation from True Elasticities

	Aggregate	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5
Brand 1	0.37 (1)	0.57 (41)	0.49 (12)	0.31 (11)	0.26 (8)	0.20 (6)
Brand 2	0.37 (2)	0.58 (29)	0.58 (15)	0.31 (17)	0.26 (5)	0.21 (3)
Brand 3	0.36 (0)	0.49 (35)	0.52 (1)	0.46 (5)	0.25 (5)	0.21 (6)
Brand 4	0.39 (12)	0.47 (34)	0.51 (5)	0.30 (12)	0.41 (18)	0.19 (6)
Brand 5	0.29 (0)	0.48 (32)	0.53 (3)	0.30 (11)	0.24 (5)	0.24 (4)
Brand 6	0.37 (2)	0.46 (33)	0.59 (6)	0.31 (12)	0.25 (4)	0.19 (6)

Table 5: Estimated Equilibrium Margins for Aggregate Market and (Percentage Absolute Deviation from True Margins)

Attributes	Manufacturer Stackelberg					
	seg 1	se 1	seg 2	se 2	seg 3	se 3
price ($/oz)	-44.58	2.20	-94.46	2.20	-214.14	4.68
ad	0.15	0.16	1.16	0.16	0.02	0.36
display	0.47	0.15	0.75	0.15	0.56	0.33
Heinz 32	-0.65	0.14	1.88	0.14	3.65	0.53
Hunts 32	-0.67	0.15	-0.27	0.15	5.39	0.52
Heinz 28	0.05	0.19	1.92	0.19	1.64	0.42
Heinz 44	-1.09	0.21	-1.03	0.21	3.45	0.79
store 1	0.91	0.07	0.91	0.07	0.91	0.07
store 2	0.02	0.06	0.02	0.06	0.02	0.06
store 3	0.48	0.06	0.48	0.06	0.48	0.06
store 4	-0.65	0.07	-0.65	0.07	-0.65	0.07
store 5	0.29	0.07	0.29	0.07	0.29	0.07
store 6	0.24	0.06	0.24	0.06	0.24	0.06
store 7	-0.59	0.08	-0.59	0.08	-0.59	0.08
store 8	0.49	0.06	0.49	0.06	0.49	0.06
prob	0.33	0.02	0.37	0.02	0.30	
GMM objective (degrees-of-freedom)	0.00021977 (42)					

Table 6: Estimated Demand Parameters (MS model)

Attributes	Vertical Nash					
	seg 1	se 1	seg 2	se 2	seg 3	se 3
price ($/oz)	-133.68	0.56	-65.74	3.59	-26.97	1.34
ad	0.84	0.05	0.70	0.06	0.77	0.05
display	0.74	0.07	0.61	0.08	0.63	0.07
Heinz 32	1.59	0.08	0.86	0.21	0.55	0.16
Hunts 32	1.55	0.09	0.28	0.25	-0.51	0.19
Heinz 28	1.74	0.11	1.17	0.27	0.77	0.23
Heinz 44	-0.53	0.40	-1.12	0.51	-0.11	0.92
store 1	1.14	0.07	1.14	0.07	1.14	0.07
store 2	0.02	0.06	0.02	0.06	0.02	0.06
store 3	0.64	0.06	0.64	0.06	0.64	0.06
store 4	-0.82	0.07	-0.82	0.07	-0.82	0.07
store 5	0.34	0.07	0.34	0.07	0.34	0.07
store 6	0.28	0.06	0.28	0.06	0.28	0.06
store 7	-0.75	0.08	-0.75	0.08	-0.75	0.08
store 8	0.66	0.06	0.66	0.06	0.66	0.06
prob	0.67	0.04	0.23	0.03	0.11	.
GMM objective (degrees-of-freedom)	0.00067566 (42)					

Table 7: Estimated Demand Parameters (VN model)

Attributes	Nested Logit					
	seg 1	se 1	seg 2	se 2	seg 3	se 3
price ($/oz)	-37.28	0.00	-76.83	0.47	-229.72	0.12
ad	0.25	0.14	1.17	0.34	0.17	0.31
display	0.65	0.12	0.69	0.28	0.78	0.26
Heinz 32	-0.84	0.08	1.02	0.20	3.94	0.16
Hunts 32	-1.07	0.05	-0.71	0.05	5.93	0.05
Heinz 28	-0.65	0.13	1.37	0.38	0.45	0.74
Heinz 44	-1.56	0.046	-1.49	0.05	4.73	0.06
store 1	0.91	0.06	0.91	0.06	0.91	0.06
store 2	0.02	0.06	0.02	0.06	0.02	0.06
store 3	0.49	0.06	0.49	0.06	0.49	0.06
store 4	-0.64	0.07	-0.64	0.07	-0.64	0.07
store 5	0.29	0.06	0.29	0.06	0.29	0.06
store 6	0.25	0.06	0.25	0.06	0.25	0.06
store 7	-0.59	0.08	-0.59	0.08	-0.59	0.08
store 8	0.52	0.06	0.52	0.06	0.52	0.06
prob	0.33	0.03	0.37	0.00	0.30	
sigma	0.01	0.00				
GMM objective (degrees-of-freedom)	2.1741e-004 (42)					

Table 8: Estimated Demand Parameters (MS and nested logit model)

Marginal Cost Function	param	se	median mc $/oz
Heinz 32	-0.373	0.021	0.007
Hunts 32	-0.356	0.021	0.024
Heinz 28	-0.374	0.021	0.006
Heinz 44	-0.371	0.021	0.009
labor	0.005	0.001	
container (*10E-3)	0.384	0.074	
ingredients (*10E-3)	30.466	1.670	

Table 9: Marginal Cost Function and Median Cost Estimates (MS model)

Marginal Cost Function	param	se	median mc $/oz
Heinz 32	-0.091	0.010	0.000
Hunts 32	-0.079	0.009	0.012
Heinz 28	-0.092	0.010	-0.001
Heinz 44	-0.113	0.010	-0.021
labor	0.002	0.000	
container (*10E-3)	0.000	0.000	
ingredients (*10E-3)	0.001	0.000	

Table 10: Marginal Cost Function and Median Cost Estimates (VN model)

Marginal Cost Function	param	se	median mc $/oz
Heinz 32	-0.230	0.035	0.000
Hunts 32	-0.204	0.035	0.026
Heinz 28	-0.233	0.034	-0.003
Heinz 44	-0.210	0.035	0.019
labor	0.002	0.001	
container (*10E-3)	0.000	0.000	
ingredients (*10E-3)	0.002	0.000	

Table 11: Marginal Cost Function and Median Cost Estimates (MS and nested logit model)

	Out-of-sample RMSE	
	eqbm. prices	eqbm. shares
MS	0.006	0.023
VN	0.006	0.027
MS nested logit	0.006	0.027

Table 12: Out-of-sample Mean-square Error for comparison models

	Manufacturer Stackelberg (MS) Retailer Margin %	Vertical Nash (VN) Retailer Margin%	MS with Nested Logit Retailer Margin %
Heinz 32	38.1	60.2	47.4
Hunts 32	32.4	61.9	34.3
Heinz 28	40.0	50.8	43.3
Heinz 44	47.7	55.1	48.1
Category Avg.	39.5	57.0	43.3

Table 13: Retailer Margins (percentage of retail price) Estimated by the Three Models