Strategic Implications of Retail Pricing in the U.S. Fluid Milk Market*

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Abstract: We explore brand level strategic interactions between skim/low fat and whole milk brands by estimating detailed price elasticity matrix using quadratic almost ideal demand system for eight major U.S. cities. Results of our analysis suggest that the market and demand behavior of skim/low fat and whole milk brands are different. Demand for skim/low fat milk is more elastic than in the case of whole milk. Highly inelastic demand for large number of Private label whole milk brands suggests 'loss leader' pricing strategy by the retailers. Such pricing strategy does not seem to be the norm in skim/low fat milk market.

Keywords: Quadratic almost ideal demand system, fluid milk, loss leader, skim/low fat milk, whole milk.

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1. Introduction

U.S. fluid milk markets are going through radical changes in terms of increasing concentration through mergers and acquisitions in the processing and retailing sectors. Our analysis, using proprietary IRI data, suggests that 4 firm concentration ratios in major U.S. cities can vary from 85% to 99%. By any standard, these concentration numbers are high. Also the relationships between pricing of top brands can also be quite complex. In some cities pricing of branded milk is highly correlated. For example, in one of the North East cities we find correlation coefficient between branded milks to be as high as 0.90. On the other hand, in one Midwestern city, the average correlation coefficient between branded milks is 0.75. Given this potential disparity in pricing mechanisms, it is important for us to understand the nature and causes of price determination in fluid milk market as part of the foundations for better public policy initiatives.

Fluid milk processors and retailers in New England have recently come under increased scrutiny from state and federal regulatory agencies because of their alleged anti-competitive market conduct (Cotterill et-al., 2002). Our preliminary estimates of concentration across major U.S. cities are not really that different from the New England cities. So, comprehensive research involving major cities across the U.S. is rather important at this point. Such disaggregated city level study is also important for policy analysis due to changes in Federal milk marketing order program (FMMO). Until now most FMMO policy simulations have used highly aggregated national or regional data and assuming a competitive market structure. By exploring different city level fluid milk markets using disaggregated data we plan to generate the empirical foundations for future research in FMMO policy simulation modeling based on disaggregated data and regional marketing behavior under assumptions of imperfect competition.

In analyzing strategic market behavior economists have always been concerned about the impact of aggregation. Specifically in market level analysis, if different segments of the market behave differently then aggregation will not only hide the underlying differences but also may distort the findings for particular markets. Here we should mention that the data we are using is also aggregated. Our IRI database is aggregated at the city level. But compared to most previous studies on the U.S. fluid milk market we are using more disaggregated data. This level of disaggregation allowing to explore market level behavior of brands within a city and can provide a view of strategic competition from the perspective of a brand manager. As more disaggregated data becomes available, we will explore issues related to strategic behavior using such data. For example, with retail chain level data within a city it is possible to explore brand level competition within a store, a perspective comparable to the view of pricing/brand competition from the perspective of a category manager within a supermarket.

To the best of our knowledge this is the first paper to explore strategic behavior in fluid milk markets for 8 major U.S. cities using a single methodology. This allows for a more meaningful comparison across the different cities. These cities are geographically dispersed and vary in terms of size from medium to large. Recently, studies by Dhar and Cotterill (2002) and Cotterill et-al. (2002) have explored similar strategic behavior issues as explored here, but only for the New England (mainly Boston) market. The approach used in this paper will be similar to that used in the papers mentioned above in that we use highly disaggregated data.

While we explore strategic behavior across 8 U.S. cities using highly disaggregated data, space constraints limit the exploration of all the dimensions of strategic price competition in U.S. fluid milk markets. One issue of specific interest is the nature and differences in price competition between skim/low fat and whole milk markets. Most studies and policy debates usually assume that the nature of competition in these two markets is the same. One of the reasons for this assumption is the fact that the retail prices between skim/low fat and whole milk is highly correlated. As a result firms are assumed to be pricing their skim/low fat milk and whole milk by the same pricing rules. A more practical reason is to avoid major computational burdens using complex demand models, where aggregating skim/low fat and whole milk data in earlier studies helped to avoid 'curse of dimensionality' problems associated with estimating large, disaggregated structural models. Thanks to recent computing advances, we estimate complex, disaggregated brand level demand models with large numbers of parameters with good accuracy and within a manageable time frame. In particular, we model and estimate brand level skim/low fat and whole milk demands separately and explore similarities and differences in the competitive pricing between these markets. If these two markets behave in the same way, then the estimated demand system should have similar behavioral patterns in terms of own and cross price elasticities.

We use the quadratic almost ideal demand system (Q-AIDS) developed by Banks, Blundell and Lewbel (1997) to estimate detailed and disaggregated brand level demand systems for these regional milk markets. Q-AIDS is a highly flexible and theoretically consistent demand system and is a significant over traditionally used AIDS.

The organization of this paper is as follows. In section 2 we briefly discuss our databases and the level of aggregation that we use. In section 3 we present our demand model and in section 4 we explain estimation procedure for estimating such demand system. Section 5 presents our empirical demand specification. And section 6 discusses the results and in the last section 7 we present our concluding remarks.

2. Data and Descriptive Statistics

We use retail scanner data from Information Resources Inc. to conduct exploratory market analysis and to estimate our demand system. Our scanner database provides brand level milk prices and sales weekly from week ending 3/9/1997 to week ending 2/24/2002 collected so as to be representative of the markets in our 8 cities. This IRI scanner database provides detailed brand and processor level information on sales and other merchandising information. We augment this database with wholesale level, administered milk price data from Federal Milk Marketing Order. In the case of Private Labels the database only identifies them by the retailers but not by the processor. So, we treat Private Label by a retailer as a brand in itself. In this paper we are interested in strategic issues, so to keep the analysis manageable we estimate our demand system using only the brands with at least 5% market share. Rest of the fringe brands are aggregated as an All-Other brand. So, in the demand analysis the number of brands varies from city to city based on this criterion. Next, we will present descriptive statistics of the variables used in our analysis.

To give an idea of market size of each market we rank the cities by percentage of total population in the 8 cities. Total population in these 8 cities is 29.25 million. Based on population we rank the cities and sort all the tables presented in this paper by the ascending order. So, the first city in any table is the smallest city and the last one is the largest. Due to confidentiality agreement with IRI we can not provide detailed information on specific city. Of these cities, 1 is from the Northeast census region (termed as NE_1 in the paper), 2 are from the Midwest (e.g. MW_1 and MW_2), 3 are from the West census region and 2 are from the South census region.

In tables 1 and 2 we present descriptive statistics of the variables used in our analysis. The average per gallon price of whole milk is highest in the West ($3.49/ gal) and lowest in the South ($2.48 /gal). For skim/low fat milk, the highest price is in the South ($3.16) and the lowest is in the West ($2.36). We are unable to discern patterns between city size and any of the variables presented in these two tables. The patterns between whole milk and skim/low fat milk are somewhat clearer. The price of skim/low fat milk on an average is lower than the price of whole milk, partly reflecting a lower value due to lower fat content under FMMO pricing. In terms of packaging (i.e. volume per unit) whole milk tends to sell in larger package sizes. Similarly in the case of percentage volume sold through merchandising and the percentage of any price reduction (two of the proxy for marketing mix variables used in our regression analysis), we do not find any specific pattern across cities. We discuss some of these descriptive statistics in details in the section 3 of the paper.

3. A Consumer Demand System for Multiple Milk Brands

In this section we first describe our choice of demand system. Then we derive the analytical form of the post estimation measures and the price and expenditure elasticities.

a. *Quadratic Almost Ideal Demand System:*

To specify demand for different types of milk we use the quadratic almost ideal demand system (Q-AIDS). Our non-parametric analysis of Engel curves suggests that relationship between per capita expenditure on any milk type and total per capita expenditure on milk is non-linear. Banks, Blundell and Lewbel (1997) have shown that in the presence of such non-linear Engel curves use of rank 2 (for example: AIDS) demand system is inappropriate. The Q-AIDS is the best available exactly aggregable demand system to capture any non-linear impacts of price and expenditure changes on demand. The demand generated by the Q-AIDS is of rank 3 which, as proved in Gorman (1981), is the maximum possible rank for any demand system that is linear in functions of income. Unlike the AIDS model (Deaton and Muelbauer, 1981) and the exactly aggregable Translog model of Jorgenson et al. (1982) the Q-AIDS model permits goods to be luxuries at some income level and necessities at others.

Here, we first describe the derivations of a Q-AIDS demand system. Let *e(p, u)* be the household expenditure function, where $p \in R^n_{++}$ is the ($n \times 1$) price vector of the ($n \times 1$) vector of consumption goods $q \in R^n_+$. Under the almost ideal class of demand systems, $\ln e(p,u) = \ln a(p) + c(p)\left[d(p) + u^{-1}\right]^{-1}$, where:

$\ln a(p) = \alpha_0 + \alpha^T \ln p + 0.5(\ln p)^T \Gamma(\ln p)$, $\ln c(p) = \beta^T \ln p$, and $d(p) = \tau^T \ln p$. Denote by k_n the ($n \times 1$) vector $\begin{bmatrix} \mathrm{k} \\ \vdots \\ \mathrm{k} \end{bmatrix}$. The parameters $(\alpha, \beta, \tau, \Gamma)$ satisfy the restrictions:

$\alpha^T 1_n = 1$, $\beta^T 1_n = 0$, $\tau^T 1_n = 0$, $\Gamma\, 1_n = 0_n$ (homogeneity/adding up), and $\Gamma^T = \Gamma$ (symmetry). Letting $M > 0$ be household expenditure corresponding, the Marshallian demand specification in terms of expenditures shares $w \equiv (p_1 q_1^*/x, \ldots, p_n q_n^*/x)^T$ are

(1) $\quad w = \alpha + \Gamma \ln p + \beta [\ln x - \ln a(p)] + \tau [\ln x - \ln a(p)]^2/c(p)$.

In order to facilitate the empirical implementation one can also specify this demand specification in summation notation as:

$$(2)\qquad w_{ilt} = \alpha_i + \sum_{j=1}^{N} \gamma_{ij} \ln(p_{jlt}) + \beta_i \ln\left(M_{lt}/P_{lt}\right) + \frac{\tau_i}{\prod_{i=1}^{N} p_{ilt}^{\beta_i}} \left[\ln\left(M_{lt}/P_{lt}\right)\right]^2$$

where $p = (p_1, \ldots, p_N)'$ is a $(N\times 1)$ vector of prices for q, and $w_{ilt} = (p_{ilt}\, x_{ilt}/M_{lt})$ is the budget share for the i^{th} commodity consumed in the l^{th} city at time t. The term P, the price index can be expressed as: $ln(P_{lt}) = \delta + \sum_{m=1}^{N} \alpha_m\, ln(p_{mlt}) + 0.5 \sum_{m=1}^{N} \sum_{j=1}^{N} \gamma_{mj}\, ln(p_{mlt})\, ln(p_{jlt})$.

The above AIDS specification (equation 2) can be modified to incorporate the effects of socio-demographic variables ($Z_{1lt}, \ldots, Z_{Klt}$) on consumption behavior, where Z_{klt} is the k^{th} socio-demographic variable in the l^{th} city at time t, $k = 1, \ldots, K$. This method, demographic translating, allows demographic differences to shift both the intercept and elasticity parameters. Under demographic translating, α_i is assumed to take the following form: $\alpha_{ilt} = \alpha_{0i} + \sum_{k=1}^{K} \lambda_{ik} Z_{klt}$, $i = 1, \ldots, N$.

b. Using Q-AIDS to analyze substitution between milk types:

From the estimating a Q-AIDS model, one can recover detailed compensated and un-compensated own and cross price elasticities, expenditure elasticities, and measures of consumer welfare. The own and cross price elasticities allow us to analyze the substitution behavior of consumers between the different types of milk as a way of describing consumer demand for labeled milk. In addition, the literature suggests that labeled milk should be a luxury good, a proposition which can be approximately analyzed with the expenditure elasticity. Together these elasticities describe the patterns of consumer willingness to pay for labeled milk.

Differentiating the demand system (equation 1) *w.r.t.* ln*p* and ln*M* we get price and expenditure elasticity measures. Let $\mu_i = \frac{\partial w_i}{\partial \ln m} = \beta_i + \frac{2\lambda_i}{b(P)}\left\{\ln\left[\frac{m}{a(P)}\right]\right\}$ and

$$\mu_{ij} = \frac{\partial w_i}{\partial \ln p_j} = \gamma_{ij} - \mu_i\left(\alpha_j + \sum_k \gamma_{jk} \ln p_k\right) - \frac{\lambda_i \beta_j}{b(p)}\left\{\ln\left[\frac{m}{a(p)}\right]\right\}^2$$

. Then the expenditure elasticities are given by: $e_i = \frac{\mu_i}{w_i} + 1$. The uncompensated price elasticities are given by $e_{ij}^u = \frac{\mu_{ij}}{w_i} - \delta_{ij}$ where δ_{ij} is the Kronecker delta.

4. Estimation Procedures for the Demand System

A number of previous studies have found problems with the endogeneity of price and expenditure in estimating demand systems using aggregate scanner data such as those used in this study (see e.g., Dhar, Chavas and Gould, 2003). Thus, our estimation procedure for the Q-AIDS demand system, equation (2), needs to include an additional set of equations to control for endogeneity of the prices and expenditures.[i] We estimate our demand equations, reduced form price equations, and expenditure equation using a full information maximum likelihood estimation method. Due to adding up restrictions of the Q-AIDS demand system we drop one demand equation and estimate a system with N-1 demand equations, N reduced form price equations, and 1 expenditure equation, where N is the number of brands with market shares greater than 5%.

The reduced form price equations used to control for price endogeneity for each milk brands are specified to capture the supply side of the price formation mechanism. The price equation for the i^{th} commodity in the l^{th} city at time t is:

(5) $p_{ilt} = f(supply/demand\ shifters)$.

In equation (5) supply/demand shifters would include variables to describe raw material, product manufacturing, and packaging costs. Following Blundell and Robin we specify a reduced form expenditure equation where household expenditure in the l^{th} city at time t is a function of median household income and a time trend:

(6) $$M_{lt} = f(\textit{time trend, income}).$$

Given these reduced form specifications for the price and expenditure equations, we estimate jointly (2), (5) and (6) by FIML. The resulting parameter estimates have desirable asymptotic properties (Amemiya).

To control for city specific variations, we modify the Q-AIDS specification with demographic translating variables ($Z_{1lt}, \ldots, Z_{Klt}$). As a result, our AIDS model incorporates a set of seasonal dummy variables along with socio-demographic variables. To control for seasonal differences by city we incorporate four seasonal dummy variables in each of the Q-AIDS equations. Also to maintain theoretical consistency of the AIDS model, the following restrictions are applied to demographic translating parameter α_{0i}:

(7) $$\alpha_{0i} = \sum_{r=1}^{4} d_{ir} D_r\,,\ \sum_{r=1}^{4} d_{ir} = 1\,,\ i = 1, \ldots, N,$$

where d_{ir} is the parameter for the i^{th} brand associated with the seasonal dummy variable D_r for the r^{th} season. Note that as a result, our demand equations do not have intercept terms.

5. Empirical Specifications

Translating

Our translating specification (e.g. $\alpha_{ilt} = \alpha_{0i} + \sum_{k=1}^{K} \lambda_{ik} Z_{klt}$) has four quarterly dummies and two continuous variables. These two variables are: the monthly wage rate in the city and the consumer price index. The seasonal dummies will be able to capture any seasonal variations in a given city. The wage rate variable captures any impact of change in income on milk consumption. And lastly the consumer price index can capture any exogenous shocks in other markets on the consumption of milk.

Price Specification

Most recent studies of differentiated products have modeled price as a function of supply and demand shifters, assuming these shifters are exogenous to the price formation mechanism (e.g., Cotterill, Franklin and Ma; Cotterill, Putsis and Dhar; and Kadiyali, Vilcassim and Chintagunta). On average raw milk prices tend to be ~60% of the retail milk prices.[ii] Other retailing and processing costs include merchandising and packaging costs. Therefore we specify the price functions, equation (5), with raw milk price, marketing and other product characteristics as explanatory variables:

(8)

$$\ln(p_{ilt}) = \theta_{i0} + \theta_{i1}\ln(C\_p_{ilt}) + \theta_{i2}\left[\ln(C\_p_{ilt})\right]^2 + \theta_{i3}\ln(wage_{lt}) + \theta_{i4}\ln(p_{ilt-1}) + \theta_{i5}PRD_{ilt} + \theta_{i6}UPV_{ilt}$$

where p_{ilt} is the price of milk type i, in city l and at time t. C_p_{lt} is the price of announced cooperative class I milk price in city l at time t. Similarly, $wage_{lt}$ is the wage rate in city l at time t. p_{ilt-1} is the lagged retail price.[iii] And UPV_{ilt} in is the unit volume of the i^{th} product in the l^{th} city at time t and represents the average size of the purchase. For example, if a consumer purchases only one gallon bottles of a brand, then unit volume for that brand will be just one. Conversely, if this consumer buys a half-gallon bottle then the unit volume will be 2. This variable is used to capture packaging-related cost variations, as smaller package size per volume implies higher costs to produce, to distribute and to shelve. The variable PRD_{ilt} is the percent price reduction of brand i and is used to capture any costs associated with specific price reductions (e.g., aisle end displays, freestanding newspaper inserts).

Expenditure

Similarly the reduced form expenditure function in (6) is specified as:

(9) $\ln(x_{lt}) = \psi_0 + \psi_1 TR_t + \psi_2 \ln(x_{lt-1}) + \psi_3 \ln(wage_{lt}) + \psi_4 C\_idx_{lt}$ $t = 1, \ldots, 260.$

where ψ_0 is the intercept term. TR_t is a linear trend, capturing any time specific unobservable effect on consumer milk expenditures. The variable $wage_{lt}$ is the average wage rate in city l and is used as a proxy to capture the effect of income differences on milk purchases. C_idx_{lt} is the city level consumer price index; this variable captures any city level overall supply shocks to consumers.

We assume the demand shifters and the variables in the reduced form price and expenditure specification are exogenous. In general the reduced form specifications (i.e. equation (8) and (9)) are always identified, although the issue of parameter identification is rather complex in such a non-linear structural model.[iv] We checked the order conditions for identification that would apply to a linearized version of the demand equations (2) and found them to be satisfied. Finally, we did not encounter numerical difficulties in implementing the FIML estimation. As suggested by Mittelhammer, Judge and Miller (p.474-475) we interpret this as evidence that each of the demand equations is identified.[v]

6. Empirical Results

From tables 1 and 2 we find that, on an average, the level of merchandising and price reduction is higher in skim/low fat milk than in whole milk. This suggests that the nature of competition is more intense in skim/low fat milk than in whole milk and/or that skim/low fat milks are used as loss leaders. Further exploration of the nature of competition between whole and skim/low fat milk market segments requires us to use the results from our regression analysis.

In tables 3 and 4 we provide average own and cross price elasticities across cities. Due space limitations we do not provide detailed regression nor the elasticity estimate results by city.[vi] For all cities, own price elasticities are more elastic for skim/low fat milk than for whole milks. Average own price elasticity across cities for whole milk is -1.39 and for skim/low fat milk is -2.21. Tables 3 and 4 also summarize minimum and maximum for the own price elasticity estimates. Again we find a lower spread in the case of skim/low fat milk than in the case of whole milk. Our estimated own price elasticities in the case of skim/low fat milk are all significant at the 5% level, but this is not the case for whole milk brands. Highlighted elasticity estimates in the maximum and minimum columns of Tables 3 and 4 are all significantly different from zero at the 5% level.

We can also look at the nature of competition by the magnitudes of the estimated cross price elasticities. Again we find the similar pattern. Average cross price elasticies for skim/low fat milk are slightly larger (0.28) than for whole milk (0.23). Following a business literature rule of thumb that cross price elasticities greater than 0.5 significant competition (Keat and Young, p. 121). Except in our smallest market (Midwest), we do not find average cross price elasticities to be greater than 0.5.[vii]

Next, we explore the nature of pricing competition based on our estimated mark-ups. In literature on differentiated product markets Bertrand competition is usually accepted as the best approximation of market competition (Nevo, 2001). So, in this paper we estimate non-competitive markups assuming Bertrand competition. In a differentiated product market for a single brand, Bertrand mark-ups can be stated as: $\frac{p-c}{p} = -\frac{1}{\eta_{ii}}$,

where p is retail price, c is marginal cost and η_{ii} is the own price elasticity. We only estimate Bertrand markups in the case where own price elasticities are greater than one in absolute value, i.e., where demand is elastic. In a non-competitive market inelastic demand implies marginal revenue to be negative. A profit maximizing firm will not produce at a level where marginal revenue becomes negative. So, estimating any form of profit maximizing markups where firms are selling in the inelastic portion of the demand function is meaningless.

We also estimate an upper bound markup based on the available data. Our database contains retail price and cooperative milk price data. So we estimate the upper bound as: $\frac{RP - COOP}{RP}$, where RP is the retail milk price and $COOP$ is the cooperative milk price. In the supermarket fresh milk category, raw milk prices tend to be 62% of the total milk price.[viii] Actual channel markups should be less than this estimated upper bound raw markup as shelf milk also includes other costs. So, we eliminate any estimated Bertrand markup that is greater than estimated raw markup upper bound. In terms of raw markup, the average raw markup for skim/low fat milk is 0.49 and for whole milk is 0.52. In the case of Bertrand markup, it is 0.37 for skim/low fat and 0.38 for whole milk. The estimated Bertrand markup is quite high compared to the upper bound, suggesting processors with profit objectives tend to make significant profits in these markets. These average mark-ups also do not suggest any major differences in the markets for skim/low fat and whole milk, implying aggregation of markups at this level are likely hiding the distinct differences in pricing and demand that are indicated by the elasticity estimates.

In tables 3 and 4 we also provide the number of brands that have inelastic brand demands. There are more brands in the whole milk category (19 brands) that have inelastic demand compare to 8 skim/low fat milk brands (8 brands). All these inelastic brands are Private Labels. We know the theory of profit maximization firms do not maximizes profits when the demand is inelastic. If a firm is selling at the inelastic portion of the demand function this implies the firm is either building market share treating this product as loss leader or building store traffic with this brand or product. This implies Private Label brands are used more prominently as strategic baits by retailers to attract consumers, i.e., in marketing jargon Private Labels can be termed as 'loss leaders'.

To show the differences more clearly we present in tables 5 and 6 detailed estimated elasticities for two of the comparable representative cities. They are NE_1 and MW_1. These 2 cities are comparable in terms of size and market concentrations (market concentration numbers are presented in table 7). But based on brand level elasticity estimates they are quite different. In both markets branded milks are significantly elastic with higher elasticities for skim/low fat milk. In the case of Private label, we get very different results. In NE_1, one private label skim/low fat and all the private label whole milk have inelastic demand. This is not the case in MW_1. In MW_1 all the private labels have elastic demand. But here also, private label whole milk brands are less elastic than skim/low fat milk.

We do not find any specific pattern of own and cross price elasticities across cities based on market size. In I/O literature it is also common explore strategic market differences using market concentration indices. So, we develop different measures of concentration across cities and explore relationships between concentration measures and elasticity estimates in tables 3 and 4. Concentration measures are the main building blocks in exploring market structure and conduct under structure conduct-performance (SCP) methodology in industrial organization literature. We measure concentrations both at the retail and at the processor level. Our different measures of concentration are presented in

Table 7. Our database does not allow us to identify any specific Private Label processors. So, in calculating measures processors level concentrations we total Private Label volume sales as a single entity.[ix] Based on this assumption we estimate three measures of processor level concentration: the Herfindahl-Hirschman index (HHI), CR_4 and CR_2. The IRI database also provides major retail chains Private Label volume sales data. So, in column 5 table 7 we provide the number major Private Label brands in that market. And, in column 6 we provide information on Private Label share of the total market.

To get an indication of the independent processor level market share, we provide market share of the top 2 processors in any given market. In terms of Private Label share the largest share (82%) is in the West and the lowest share (39%) is in the Midwest. Similarly we calculate the share of the top 2 brands. We explore relationships between elasticity measures and different measures of market concentration using different exploratory data analysis methodology (such as: ANOVA, cluster analysis). We are unable to discernible any meaningful relationships.

By any measure, the concentration in these markets is significantly high. The theory of differentiated product oligopolistic markets suggests that, in any highly concentrated market, strategic behavior of market players can be quite involved. So it is not surprising that we do not find any meaningful relationships between estimated elasticity measures and concentration measures at the aggregated (versus) branded market level.

7. Concluding Remarks

Our analysis in this paper does suggest significant differences in the nature of demand for skim/low fat and whole milk. Overall the whole milk market is much less price responsive.

A lot of the brands are sold at a price level where demand is inelastic, suggesting a loss leader pricing strategy by channel players. On the other hand skim/low fat milk markets are more strategically competitive. This result conforms to the anecdotal evidence from the market. Large families and families with children tend to consume more whole milk. So, to attract these consumers, retailers can use whole milk as loss leader. It is known that high income consumers tend to be much more health conscious and as a result they tend to consume more skim/low fat milk. So, skim/low fat milk can be priced much more strategically.

In recent New Empirical Industrial Organization literature it is argued that strategic behavior in the market can be best analyzed using disaggregated data and estimating detailed brand level demand models. Such demand models provide detailed strategic inter relations between brands based on estimated own and cross price elasticities (Nevo, 2001) and provide insights into consumer welfare (Hausman and Leonard, 2002; Dhar and Foltz, 2003). Our multi-market analysis also suggests that results and inferences based on aggregated concentration and margin indices may hide such strategic inter relationships between different brands. Hence, we find evidence that milk market analysis with aggregated data can be problematic as there are rich patterns of strategic behavior in different markets hat are likely to remain hidden. In particular, our analysis shows that the Skim/low fat and whole milk brands behave differently in the market place. Given significant differences in the skim/low fat and whole milk markets, in future research and policy analysis these differences should be taken into account. .

Table 1: Average Price and other Scanner Data Descriptive by City [S/L Milk]

City	Price (Whole)	Vol. per Unit	% vol Merchandisin	% vol Price Reduction	Market Share	COOP Milk Price
WE_3	2.36	0.92	30.8	20.8	0.86	1.3
MW_2	2.66	0.8	19.3	11.6	0.75	1.4
WE_2	3.01	0.73	24.9	27.9	0.84	1.3
WE_1	2.59	0.83	42.9	25.2	0.77	1.3
SO_2	3.16	0.84	14.7	22.7	0.64	1.5
SO_1	2.55	0.81	33.8	22.5	0.55	1.4
NE_1	2.90	0.71	15.9	13.4	0.69	1.5
MW_1	2.92	0.81	24.9	22.1	0.78	1.4

Table 2: Average Price and other Scanner Data Descriptive by City [Whole Milk]

City	Price (Whole)	Vol. per Unit	% vol Merchandising	% vol Price Reduction	Market Share	COOP Milk Price
WE_3	2.81	0.85	14.60	14.26	0.14	1.30
MW_2	2.89	0.78	13.84	10.73	0.25	1.39
WE_2	3.49	0.67	11.97	23.87	0.16	1.35
WE_1	2.74	0.81	24.26	20.09	0.23	1.35
SO_2	3.13	0.79	14.59	21.12	0.36	1.49
SO_1	2.48	0.84	30.19	27.65	0.45	1.43
NE_1	2.90	0.71	7.45	11.23	0.31	1.46
MW_1	3.01	0.78	27.49	23.16	0.22	1.42

Table 3: Average Elasticity Measures by City-Skim/low fat Milk

City	No. of Brands	No. of PL	Own Price Elasticity	Min Own Price	Max. Own Price	No of Processors >-1	Cross Price El	Bertrand-Markups	Raw Mark-ups
WE_3	5	2	-1.98	**-1.30**	**-3.68**	0	0.31	36%	50%
MW_2	5	1	-2.32	**-1.19**	**-5.76**	0	0.52	24%	51%
WE_2	4	2	-1.01	**-1.01**	**-3.73**	0	0.22	35%	44%
WE_1	5	3	-1.29	**-1.27**	**-4.65**	0	0.33	42%	53%
SO_2	5	6	-2.96	**-0.28**	**-2.27**	3	0.20	45%	48%
SO_1	7	6	-3.26	**-0.17**	**-1.69**	4	0.10	-	55%
NE_1	7	4	-1.74	**-0.33**	**-3.60**	1	0.20	46%	45%
MW_1	4	3	-3.10	**-1.04**	**-4.46**	0	0.36	33%	48%

Table 4: Average Elasticity Measures by City-Whole Milk

City	No. of Brands	No. of PL	Own Price	Min Own Price	Max. Own Price	No of Processors >-1	Cross Price El	Bertrand-Markups	Raw Mark-ups
WE_3	5	2	-1.39	-0.40	**-3.11**	2	0.28	32%	50%
MW_2	5	1	-1.85	-0.36	**-5.21**	1	0.60	39%	53%
WE_2	4	2	-0.97	0.03	**-1.79**	2	0.03	56%	42%
WE_1	5	3	-0.75	**-0.60**	**-2.96**	2	0.25	34%	52%
SO_2	5	6	-1.42	-0.14	**-1.50**	4	0.11	-	51%
SO_1	7	6	-0.79	-0.01	**-1.88**	4	0.09	-	61%
NE_1	7	4	-1.52	-0.08	**-3.34**	4	0.17	31%	54%
MW_1	4	3	-2.42	**-1.16**	**-2.98**	0	0.29	34%	52%

Table 5: Detailed Price Elasticity Matrix for NE_1

	BR_1		BR_2		PL_1		PL_2		PL_3		PL_4		All-Other	
	S/L	**W**	**S/L**	**W**	**S/L**	**W**	**S/L**	**W**	**S/L**	**W**	**S/L**	**W**	**S/L**	**W**
BR_1	**-2.27**	**-1.38**	0.69	0.38	-0.13	-0.44	0.10	-0.38	0.09	-0.16	0.19	-0.01	-0.05	-0.02
	0.24	*0.33*	*0.18*	*0.22*	*0.08*	*0.15*	*0.09*	*0.18*	*0.14*	*0.13*	*0.15*	*0.19*	*0.06*	*0.13*
BR_2	0.94	0.69	**-3.60**	**-3.34**	-0.11	0.02	0.22	0.35	0.36	0.01	0.07	0.28	0.30	0.41
	0.30	*0.34*	*0.34*	*0.32*	*0.12*	*0.26*	*0.15*	*0.20*	*0.17*	*0.15*	*0.20*	*0.29*	*0.10*	*0.21*
PL_1	-0.02	-0.27	0.09	0.15	**-0.33**	**-0.08**	0.08	-0.25	0.03	0.32	-0.18	-0.69	-0.08	0.18
	0.13	*0.21*	*0.11*	*0.20*	*0.13*	*0.25*	*0.10*	*0.17*	*0.13*	*0.15*	*0.17*	*0.21*	*0.09*	*0.10*
PL_2	0.69	-0.14	0.71	0.53	0.19	-0.18	**-1.16**	**-0.67**	0.05	0.17	0.11	0.21	-0.08	0.00
	0.14	*0.24*	*0.17*	*0.19*	*0.11*	*0.20*	*0.13*	*0.22*	*0.15*	*0.14*	*0.21*	*0.24*	*0.09*	*0.13*
PL_3	0.77	-0.03	1.45	0.31	0.12	1.06	0.05	0.50	**-3.39**	**-0.16**	0.84	-0.80	0.03	-0.31
	0.63	*0.43*	*0.51*	*0.34*	*0.36*	*0.45*	*0.37*	*0.38*	*0.90*	*0.52*	*0.73*	*0.65*	*0.33*	*0.27*
PL_4	0.56	0.31	0.34	0.33	-0.11	-0.52	-0.01	0.09	0.25	-0.31	**-1.53**	**-0.91**	0.26	0.51
	0.18	*0.18*	*0.18*	*0.16*	*0.13*	*0.18*	*0.15*	*0.18*	*0.22*	*0.19*	*0.31*	*0.34*	*0.13*	*0.12*
All-Other	-0.47	-0.13	0.28	0.63	-0.38	0.10	-0.49	-0.33	-0.12	-0.42	-0.03	1.00	**-1.57**	**-3.17**
	0.15	*0.39*	*0.15*	*0.41*	*0.12*	*0.27*	*0.11*	*0.26*	*0.16*	*0.22*	*0.23*	*0.36*	*0.20*	*0.34*

**Italicized numbers are the Standard errors.* **BR: Branded; PL: Private label; S/L: Skim/Low Fat; W: Whole*

Table 6: Price Elasticity Matrix for MW_1

	BR_1		PL_1		PL_2		All-Other	
	S/L	**W**	**S/L**	**W**	**S/L**	**W**	**S/L**	**W**
BR_1	**-4.46**	**-2.98**	0.68	0.31	2.02	0.64	-0.23	0.44
	0.56	*0.35*	*0.25*	*0.16*	*0.42*	*0.28*	*0.34*	*0.26*
PL_1	0.90	0.79	**-1.46**	**-1.39**	-0.73	-0.40	0.10	0.71
	0.25	*0.25*	*0.25*	*0.24*	*0.16*	*0.15*	*0.22*	*0.28*
PL_2	2.93	1.53	-0.46	-0.42	**-2.31**	**-1.16**	0.22	0.10
	0.49	*0.43*	*0.16*	*0.16*	*0.46*	*0.51*	*0.32*	*0.33*
All-Other	0.08	0.43	0.11	0.19	-0.16	-0.22	**-1.04**	**-1.86**
	0.19	*0.21*	*0.11*	*0.16*	*0.16*	*0.17*	*0.21*	*0.23*

**Italicized numbers are the Standard errors.* **BR: Branded; PL: Private label; S/L: Skim/Low Fat; W: Whole*

§ Elasticity estimates in each cell corresponds to η_{ij} : percentage change quantity demanded of *i* to 1% change in price of *j*.

Table 7: Concentration Measures by City

City	HHI	CR4	CR2	No. of Private	PL Share (%)	BR2 Share (%)	Pop/GS
WE_3	4,828	93.4	79.4	2	67	11	10.5
MW_2	2,706	97.7	61.9	1	39	22	9.5
WE_2	6,804	96.8	90.8	2	82	6	8.1
WE_1	6,403	99.6	96.1	3	78	10	10.1
SO_2	6,062	96.6	93.1	6	76	10	8.2
SO_1	5,007	96.7	85.3	6	68	12	9.9
NE_1	3,771	96.4	78.0	4	54	20	13.7
MW_1	5,435	97.0	94.3	3	69	13	12.5

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Endnotes

[i] An alternative is the GMM framework developed by Banks, Blundell, and Lewbell.

[ii] Dairy Industry: Information on Milk Prices and Changing Market Structure. U.S. G.A.O Report, January 2001.

[iii] Note that processors pay the same price to farmers for all any types of milk and this price is governed by the federal milk marketing order (FMMO).

[iv] For a detailed discussion please refer to Mittelhammer, Judge and Miller (p.474-475).

[v] Due to space limitations, we report only related econometric results. More complete reports of the results are available from the authors on request.

[vi] All the results by city are available from the authors on request.

[vii] Note, however, that at the city level there is considerable evidence of strong substitute cross price effects at the branded level for both skim/low fat and while milks. Aggregation across cites obscures these significant details.

[viii] Government Accounting Office, Report of Congressional Requesters, Dairy Industry – Information on Milk Prices and Changing Market Structure. June 2001, GAO-01-561.

[ix] We did conduct phone surveys on retailer managers to know about the source of their Private Labels. We were not highly successful in the interview processes due to the sensitive nature of the information. But from anecdotal sources we came to know that in most markets the number of Private Label processors is very low.