Imperfect Competition between Milk Manufacturers and Retailers in a Midwestern State in the U.S.

Vardges Hovhannisyan*

Kyle W. Stiegert*

*Department of Agricultural and Applied Economics
University of Wisconsin-Madison

Email: hovhannisyan@wisc.edu and kwstiegert@wisc.edu
Phone: (608) 698-4325

Selected Paper prepared for presentation at the Southern Agricultural Economics Association Annual Meeting, Corpus Christi, TX, February 5-8, 2011

Imperfect Competition between Milk Manufacturers and Retailers in a Midwestern State in the U.S.

Vardges Hovhannisyan[1]* and Kyle W. Stiegert[2]

Abstract

This manuscript studies the market conduct of the milk manufacturers and retail chains in a Midwestern state in the U.S. Following the menu approach we employ a random coefficient logit demand model to investigate several possible scenarios on the supply side. Demand estimates are obtained using both cross-sectional and time series variation in data. We also allow annual variation in consumer demographics which helps identify the coefficients of interaction between consumer demographics and product characteristics. To further enhance identification power we allow choice set of milk to vary across markets.

The results are most supportive of the conjecture that manufacturers behave competitively letting the retailers be the residual claimants. Later they may collect a part or full rents from the retailers through two-part tariffs.

Key words: Market conduct, random coefficient logit, vertical chain, imperfect competition

[1] Department of Agricultural and Applied Economics, University of Wisconsin-Madison
[2] Department of Agricultural and Applied Economics, University of Wisconsin-Madison

* Corresponding author (hovhannisyan@wisc.edu)

Introduction

The U.S. food retailing sector has been undergoing several important changes recently. First and foremost, the concentration level in the U.S. food retailing sector has been on a rise over time. Some retail chains expanded their geographic coverage both intra and inter regionally, although the measure is still lower vis-à-vis that in the manufacturing sector and non-food retailing. With potential efficiency gains from economies of scale being the major driving factor behind this new reality, the long-term implications are not clear cut (Food and Drink Weekly, 2000). Secondly, introduction of new products and product differentiation have been occurring at an increasing rate (Martinez, 2007). Finally, the introduction of the private label products (PL) further empowered the retail end of the food marketing system in their dealings against manufacturers and/or processors, while making them more flexible on the horizontal competitive landscape (Berges-Sennou et al., 2003).

In theory retailers draw some power from the changes mentioned above, however whether this translates into market power exercised remains an empirical matter that must be investigated in the context of certain products and markets. In this application we focus on milk in a Midwestern state in the U.S. based on some anecdotal evidence pointing to retailers exercising market power against upstream players in the food marketing system. The dynamics of the farm level (cooperatives) and retail prices of milk in a major city in the state under study is also supportive of this speculation (figure 1). Retail prices manifest sluggishness in their response to declining farm prices, while at certain points in time they rise faster than farm prices. Furthermore, in periods such as 2000 and early 2006 declining farm prices went hand-in-hand with rising retail prices. Given that farm level milk price constitutes a major part of the retail price and assuming that manufacturers and retailers did not incur negative cost shocks in these periods, a plausible scenario that remains is the market power exercise on the part of retailers.

Following Von Cramon-Taubadel (1997), this might be suggestive of market power. Our choice of the state is explained by a relatively high concentration in the retail sector of the two cities (markets as defined by Information Resources Incorporated (IRI)). Specifically, three large retail chains have an aggregate 70 % market share. Moreover, we observe the same chains for the entire period of my study, which allows for tracking their behavior over time.

We investigate the milk manufacturer and retailer market conduct in a context of vertical interrelationships following a seminal work by Villas-Boas (2007). This allows us to analyze the competitive behavior of the upstream players in milk supply chain even though we do not observe wholesale milk prices. More specifically, we obtain direct estimates of market power by means of Lerner Index, while previous similar studies rely on conjectural variation approach to estimate how close an economic environment is to a competitive one. We rely on a random utility discrete choice framework to model the demand for milk for it projects milk demand on its various attributes. This allows handling a potentially large number of products.[3] Moreover, modeling somewhat realistic substitution patterns across the choice set in a given market has important implications for the economic effects, which underlie the estimates of the market power. For this reason we employ random coefficient logit model for demand (BLP, 1995), which allows each consumer sampled to have certain pattern of correlation across the choice set available across markets.[4]

---

[3] Quantity demand models like AIDS (Deaton and Muelbauer, 1980), on the other hand, are plagued with the curse of dimensionality, as the budget share equations are functions of product prices employed in the system

[4] This correlation may be expressed as a function of systematic part as consumer observed demographics, as well as random part like unobserved demographics

However, unlike previous studies (Villas-Boas (2007), BLP (1995)) we utilize both cross-sectional (two cities) and time series variation (from 2001 to 2006) in market-level data. Also this is the first known study to allow annual variation in consumer demographics which will prove valuable identifying taste coefficients. Moreover, we allow the choice set to vary across markets to further enhance the identifying power of the model (Nevo, 2001). Following menu approach (Bresnahan, 1989), we make use of consistent estimates from the demand to navigate through several supply scenarios to find the best match with the data at hand.

The remainder of this manuscript proceeds as follows. The next section discusses the data used in this analysis. Methodology used to estimate the demand for types of milk along with several supply scenarios to be tested is discussed next. Estimation results follow immediately. Conclusion provides some inferences and some possible extensions of the current work.

Data

The data used in this study are provided by the Information Resources Inc. (IRI). It is a product-level dataset on weekly basis and covers all the IRI markets across the United States for the period of 2001 through 2006. The variables covered include the quantities of milk sold at the major retail chains, the total dollar amount spent, and milk fat content. We focus on a Midwestern state in the U.S., which covers two IRI city-markets.

Products are defined as combinations of manufacturer-retailer-milk fat content; this results in 57 products (table 1). The retail prices are not observed, so we use the imputed unit values[5]. Prices and quantities of milk sold are obtained by aggregating the relevant measures for the relevant four-week periods. I deflate prices from 2002 onwards using an aggregate CPI measure

[5] This is another likely source of price endogeneity caused by measurement error

for urban areas. To obtain the market shares of the goods used in the analysis and that of the outside good (non-purchase or amount of milk sold at other outlets in the same market) we define the potential market size in each city as a product of their respective populations and the per capita milk consumption in the United States in 2006. The market shares are then expressed as the ratio of the quantities of milk sold (expressed in servings, which was about 220 ounces of milk per person in a four-week period) to the potential market demand obtained above. Consequently, the share of the outside good is the difference between the overall demand and the actual market shares.

The markets in question have been rather concentrated in the period under study. Three major retailers account for around 70 % of the overall sales (two retailer chains operate in both markets). Particularly, the retailer 3 is responsible for around 35 % of this measure (Market Scope, various years), and its average share in the dataset at hand is 26.5 % (table 2). As regards the manufacturers, private labels have the biggest share (about 36%) followed by the Dean Foods (2.4 %).

The IRI dataset was supplemented by data on cost components of milk production, specifically the electricity (industrial) and gasoline prices, average wages of employees in food sector, fluid grade milk price (which provides a good estimate of the wholesale price of milk).[6] We also use the retail-level electricity prices, Federal funds effective interest rates, and the overall dollar turnover for each retailer provided by the IRI dataset. Given that it is not always possible to get finer data on cost that varies across products, we use the cost components above to instrument for prices in the estimation of the demand model.

---

[6] Data on energy, wages were collected from the official website of BLS, Energy Information Administration, and the fluid grade milk price came from the Dairy Markets website (AAE Department, UW-Madison)

Furthermore, we randomly draw 100 observations on the household income, household head's age, number of children under 18 years of age from the joint distribution of household demographics in the cities under study, which are used to model the random coefficients of marginal utility (disutility) of product attributes across consumers. Finally, we obtain the population dynamics in the two cities in question from the Market Scope in various years.

Methodology

Milk Demand Specification

We rely upon a random coefficient discrete choice utility framework to model the demand for milk given the relative ease with which these models accommodate a large number of differentiated products[7]. Moreover, allowing the taste coefficients to vary across consumers results in a more realistic substitution patterns. We assume that consumers have quasi-linear utility function (to assume away the income effects) with the corresponding indirect utility function given by

$$U_{ijt} = x_{jt}\beta_i - p_{jt}\alpha_i + \xi_{jt} + \varepsilon_{ijt} \qquad (1)$$

Here U_{ijt} is the utility that consumer i derives from product j in time t, x_{jt} represents the observed product characteristics other than milk price, such as the fat content, p_{jt} is the price of j^{th} product in market t, ξ_{jt} embeds unobserved product characteristics (referred to as quality) , and ε_{ijt} is a mean zero idiosyncratic error term distributed independently and identically across

[7] Quantity demand models such as the Almost Ideal Demand Systems (Deaton and Muellbauer, 1980), alternatively, are derived from the consumer theory, however, they are plagued with the curse of dimensionality

consumers, products and markets. We assume the underlying distribution for the latter term is type I Extreme Value, which yields a mixed logit demand specification.

Consumer taste heterogeneity is modeled as follows

$$\begin{pmatrix} \beta_i \\ \alpha_i \end{pmatrix} = \begin{pmatrix} \beta \\ \alpha \end{pmatrix} + \Psi D_i + \Lambda Z_i, \ \forall\, i \qquad (2)$$

Where α and β are the mean population parameters of the marginal utility/disutility of price and other product attributes, D_i represents the observed consumer demographics, Z_i is unobserved consumer demographics, usually following some parametric distribution, and Ψ , Λ measure heterogeneity in consumer tastes. Allowing the consumer taste coefficients to be a function of consumer demographics allows the choices across products to be correlated for each consumer. This yields realistic substitution patterns and helps overcome the Independence from Irrelevant Alternatives feature of the logit models.

Assuming each consumer purchases a unit of milk that yields the highest utility in the choice set available in the market t, one obtains the choice probability of a product j by consumer i as follows

$$P_{ijt} = e^{x_{jt}\beta_i - p_{jt}\alpha_i + c_j + c_t + \zeta_{jt}} \Big/ 1 + \sum_{m=1}^{n} e^{x_{mt}\beta_i - p_{mt}\alpha_i + c_m + c_t + \zeta_{mt}} \qquad (3)$$

Aggregating over consumers we get the market share for the product j given by:

$$s_{jt} = \int_{i=1}^{n} P_{ijt} d_i = \iiint I\left[\left(D_{it}, Z_{it}, \varepsilon_{ijt}\right) : U_{ijt} > U_{ilt} \ \forall\, l = 0, \ldots, J\right] dF_1(D)\, dF_2(Z)\, dF_3(\varepsilon) \qquad (4)$$

Own and cross price elasticity estimates are computed according to the following formulas:

$$\varphi_{jk} = \frac{\partial s_j}{\partial p_k}\frac{p_k}{s_j} = \begin{cases} \frac{p_i}{\varphi_j}\iint \alpha_i s_{ij}(1-\alpha_{ij})\alpha F_1(D)\alpha F_2(Z), if \ k = j \\ \frac{p_k}{s_j}\iint s_{ik}\alpha F_1(D)dF_2(Z), else \end{cases} \tag{5}$$

Supply Models

Following Villas-Boas (2007) we consider six alternative supply scenarios in this application, which range from a simple linear pricing to vertical collusion among milk manufacturers and retailers. The assumption of constant marginal costs allows us to obtain the manufacturer and retailer Lerner indices using demand estimates and the optimality conditions from the respective supply scenario. The competing supply models are described in what follows:

1. *Double marginalization*

This is a scenario of linear pricing, where several multi-product Nash-Bertrand oligopolistic manufacturers and retailers maximize their profits separately, with manufacturer making the first move. To solve for the optimal prices at both levels we follow backward induction obtaining the optimality conditions for the downstream players first. The retailer e in market t is characterized by the following profit function

$$\pi_{et} = \sum_{i \in I_{et}} \left(p_{it} - p_{it}^{w} - c_{it}^{e} \right) s_{it}(p) \tag{6}$$

where I_{et} represents the products in market t offered by retailer e, p_{it}^{w} is the wholesale price of product i, c_{it}^{e} is marginal cost incurred by retailer e for i^{th} product, and $s_{it}(p)$ is the i^{th} product's market share.

The profit maximizing pure-strategy Nash-Bertrand prices find their reflection in the optimality condition given by

$$s_{it} + \sum_{k \in I_{et}} \left(p_{kt} - p_{kt}^{w} - c_{kt}^{e} \right) \frac{\partial s_{kt}}{\partial p_{it}} = 0 \qquad \forall i \in I_{et}, \quad \text{for } e = 1, \ldots, n_e \tag{7}$$

with n_e being the number of active retailers in market t.

Putting together the optimality conditions for all products, it can be shown that retailer e's price over marginal cost markup in market t is

$$p_t - p_t^{w} - c_t^{e} = -\left(O_e * \Delta_{et} \right)^{-1} s_t(p) \tag{8}$$

Where O_e the ownership matrix for retailer e is, Δ_{et} is the first-order derivatives of the market shares with respect to all prices at retail-level, and * represents element by element multiplication operator.

In the same token manufacturers' price-cost margin can be shown to equal the following

$$p_t^{w} - c_t^{w} = -\left(O_w * \Delta_{wt} \right)^{-1} s_t(p) \tag{9}$$

Where c_t^{w} a vector of marginal costs incurred by manufacturer w is related to its offerings in market t, O_w reflects its ownership structure, and $\Delta_{wt(p(w))}$ is the manufacturers' response matrix given by

$$\partial s_{kt}(p(w)) \big/ \partial p_{kt}^{w} = (\partial s_{kt} / \partial p_{kt})(\partial p_{kt} / \partial p_{kt}^{w}) \tag{10}$$

Obtaining this matrix in terms observables (retail prices, actual market shares, and ownership structures) is of great importance given the difficulty of obtaining manufacturer prices in practice[8]. As shown in Villas-Boas (2000), the reaction matrix of retail prices with respect to manufacturer prices can be obtained by totally differentiating the j^{th} equation in (7) with respect to a given wholesale price p_m^w (that varies by dp_m^w) and all the retailer prices ($dp_k, k = 1,\ldots,n$), as shown below

$$\sum_{k=1}\left(\frac{\partial s_j}{\partial p_k} + \sum_i \left[O_e(i,j)(p_i - p_i^w - c_i^e)\frac{\partial^2 s_i}{\partial p_j \partial p_k}\right] + O_e(k,j)\frac{\partial s_k}{\partial p_j}\right)dp_k - O_e(m,j)\frac{\partial s_m}{\partial p_j}dp_m^w = 0$$

Putting this in matrix terms, one obtains $G\ dp - H_m\ dp_m^w = 0$. In the same vein, differentiating the remaining retailer FOC conditions with respect to p_m^w, one obtains the m^{th} column of the reaction matrix of retailer prices (Δ_{pt}) to changes in manufacturer prices as $\partial p / \partial p_m^w = G^{-1} H_m$. Finally, the manufacturer response matrix can be computed via $\Delta_{wt} = \Delta'_{pt}\Delta_{et}$. Thus, the manufacturer price-cost markup can be computed using observables and demand estimates only, which fits our research objective given that we have no data on prices charged by milk manufacturers.

2. *Hybrid model*

This is the same as the scenario above, the only difference being that retailers own private label milk. Therefore, retailers eliminate the manufacturer margin for these products. Retailer price-marginal cost markup is given by (8), while that for manufacturers is given by

$$p_t^w - c_t^e - c_t^w = -\left(O_w^h * \Delta_{wt}\right)^{-1} s_t^h(p) \qquad (11)$$

Where O_w^h is the usual manufacturer ownership matrix excluding the entries for private labels, and $s_t^h(p)$ are the shares of national brand milk

[8] Specifically, one needs to find an expression for $\partial p_{kt} / \partial p_{kt}^w$ in terms of the observables

3. Nonlinear pricing models

The two opposing models considered here are the one with manufacturers following marginal cost pricing while allowing the retailers to be the residual claimant (manufacturers later extract a part or full monopoly rents), and the other way around. In the former case manufacturer price-cost margin is 0, while retailers' markup is as follows (retailers receive the vertical markup for each product)

$$p_t - c_t^e - c_t^w = -\left(O_e * \Delta_{et}\right)^{-1} s_t(p) \qquad (12)$$

In the latter scenario, the retailers obtain 0 margins, with manufacturers being the residual claimants whose markup is determined by

$$p_t - c_t^e - c_t^w = -\left(O_w * \Delta_{et}\right)^{-1} s_t(p) \qquad (13)$$

4. Collusion at manufacturer level

This scenario assumes manufacturers acting as a unity in maximizing their joint profit, while retailers still act individually, thus receiving the same markup as in the double marginalization case given by (8). Manufacturers' markups, on the contrary, is given by (9), the only difference being in the manufacturer ownership matrix, which is now all ones.

5. Collusion at retailer level

Manufacturers obtain markups by (9), and retailers by (8), such that retailers ownership matrix is all ones.

6. Vertical collusion / monopoly

Here the manufacturers and retailers maximize their joint profit, acting as one enterprise (similar to a monopoly case). The markup is given by

$$p_t - c_t^e - c_t^w = -\left(O_1 * \Delta_{et}\right)^{-1} s_t(p) \tag{14}$$

Empirical Results

Demand is estimated via simulated GMM procedure given the market-level data in hand. Specifically, we simulate choice probabilities for each consumer sampled from the Current Population Survey from 2001 through 2006 using their demographic characteristics, such as total household income, age of the household head, and the number of children in the households under 18 years of age. Unlike most other similar studies we make use of annual variation in demographics by drawing a different sample in each year, which is crucial for obtaining statistically significant coefficients for interactions of product features and consumer demographics. For unobserved demographics we use Halton draws from the standard normal distribution (Bhat, 1999). As shown by Bhat this minimizes the simulation error while making the estimation process much faster.

To form the GMM objective function we need to construct the respective moment conditions (orthogonality conditions between the cost components and the structural error), however this is not feasible in a usual GMM framework (linearly additive errors) given that errors appear in a highly nonlinear fashion in the demand share equations. BLP (1995) provide a contraction mapping which allows obtaining the structural errors through the inversion of the demand equations. We then proceed to minimizing the GMM objective function, and repeat the process until its minimum is obtained.

Following the two-step procedure (Goldberg and Verboven, 2001) we estimate the demand model once and make use of these estimates in navigating through the supply scenarios presented above, to find the best match given the dataset at hand.

As far as the demand model prices are clearly endogenous. This stems from simultaneous determination of supply of and demand for milk as in any structural framework. Moreover, we do not observe variables like advertising, and even specialty features like organic or lactose free[9], which contribute to the price endogeneity caused by omitted variable bias. Finally, the unit prices are computed as ratio of the dollar amount spent to the amount sold of each milk product in a given market. This reinforces the price endogeneity that could be engendered by measurement error. Houseman test for price endogeneity provides a strong support for this conjecture, namely prices are endogenous (table 1). Therefore, one needs to control for endogeneity in prices in order for the estimates of demand parameters to be reliable in a statistical sense.

Following BLP (1995) we use instrumental variable approach within GMM framework to estimate demand. However, unlike them we use manufacturer and retailer cost components and product fixed effects to instrument prices[10].

Ideally prices would be instrumented using classical instrument, which is cost. However, we do not observe the wholesale prices, or the marginal costs of the manufacturers and retailers. Therefore, we use retailer and manufacturer cost components multiplied with product fixed effects (since we do not observe the exact amount of each input used in production of various products) following an approach by Villas-Boas (2007).

[9] An important share of observations has missing milk characteristics, specifically whether it is organic or lactose free. While we recognize the impact these attributes might have on milk demand, incorporating them in the analysis would be possible at the expense of forgoing the above observations.

[10]

Results from the logit specification

The results from the multinomial logit and the instrumental variable approach are presented in table 3. It can be seen that including the product fixed effects in the logit model handles the price endogeneity to a great extent (the price coefficient more than doubles in absolute value), while applying the instrumental variable approach further corrects for the upward bias in the price coefficient.

Results from the random coefficients specification

The results from the full model are presented in table 4. The majority of the parameter estimates are statistically significant with their signs conforming to our expectations. Price coefficients are mostly negative ranging from -55 to 0.8, with less than 0.01 % being positive (figure 2). Furthermore, empirical distributions of observed demographics seem to have played a more important role in determining price distribution than the parametric distribution for unobserved demographics. The mean coefficient for price is also negative which decreases in income and the age of the household head, while decreasing in the number of children below 18 years of age in the household. This implies that relatively richer, as well as older consumers tend to pay a higher price for milk, which might be explained by their possible choices of more of specialty milks, such as organic and lactose-free, and/or purchasing milk in smaller containers. The opposite situation seems plausible for households with children.

The milk fat distribution looks like standard normal (figure 3), however its mean is positive which tends to decline in income, age, and number of children (age non-significant though).

While it seems reasonable that richer people consume lower fat milk in general, at first sight it may not look so for the households with many kids. It is known that milk fat is conducive to child brain development, especially in the early ages; however we should bear on mind that all we control for is children under 18, so great many households sampled might have kids closer to 18 (we do not observe their age). Taking a closer look at figure 4 reveals that households with no or only one kid tend to purchase more of milk with higher fat content, while those with more kids tend to have disutility for fat.

The mean coefficients for fixed product characteristics (constant and fat content) are obtained via GLS regression of coefficients capturing product fixed effects on these characteristics. Chamberlains minimum distance statistic is rather high attesting to how well the product dummies represent product mean utility in the full model.

Elasticity estimates

Estimated elasticity measure from the logit and random coefficient models are presented in table 5. Own-price elasticities for the logit model (column 1) vary significantly across the milk manufacturers from the lowest -4.08 for the J&J milk to as high as -1.17 for the private labels, with the the average of -2.63 and standard deviation of 1.32. This supports the conjecture that specialty milk (such as lactose free, organic) as produced by J&J and Organic Valley are viewed as luxury products relative to plain milk. The distribution of cross-price elasticities (column 2) also varies notably by manufacturers and retailers with mean 0.017 and standard deviation of 0.031. Private labels turned out to have the highest measure which implies that these products are the most sensitive to increases in prices of national brands. Even if the logit elasticities might look realistic further analysis based on them will lileky be misleading. For instance, logit model will predict inelastic own-price elasticity (as it is proportional to own price) and subsequantly higher market power measure for private label milk irrespective of its marginal cost. Furthermore, it yields the same cross-price elasticty for a product with respect to the ones with identical market shares without regard to their characteristics.

Own-price elasticities from the random coefficient demand (column 3) manifest less variation with mean -2.72 and standard deviation of 0.29. As in the logit case, private label has the least elastic and specialty milk has the most elastic own-price measure. Cross-price elasticities are generally higher for each product vis-à-vis logit with mean 0.04 and standard deviation of 0.02. Here milk produced by a local processor and private labels are most sensitive to rising national brand prices which seems realistic.

Lerner Index estimates across milk manufacturers and retail chains

Table 6 summarizes the Lerner indices of price markups for the supply scenarios under study. The medium markups across the products range from the lowest 33.3 % in the manufacturer only collusion to as high as 84.9 % in a scenario of vertical collusion/monopoly. In cases of monopoly and retailer collusion we also obtained markup estimates above 100 % for some products in some markets, which results in negative measures of marginal cost. In manufacturer collusion for some products we obtained negative measure of Lerner index, implying marginal cost exceeded milk price.

Statistical tests for the supply scenarios

To determine the supply scenario that provides the best fit to the dataset underlying this study we perform two types of statistical testing procedures which essentially test how well the various cost components and markups estimated explain the actual retail prices (Villas-Boas, 2007). First we regress the retail prices on the retailer and manufacturer markup estimates along with the cost components and perform a joint test of the both markups being no different from one. This is performed at a product level and for linear, logarithmic, and exponential cost functions. The result of the test from the demand model with constant marginal cost provide most support to the hybrid model (2) followed by the nonlinear model with retailers being the residual claimants (3.1) . The more general model, however, picks the model 3.1 followed by the model of vertical monopoly (6) as best fit. This procedure gives a feel for how well the alternative supply models perform given the data at hand, neverthless, since one rarely knows the exact forms of manufacturer and retailer marginal cost functions we employ a more general test as proposed by Smith, 1992. It builds up on a Cox-type test statistic (Cox, 1962) of distance between the objective functions of any two competing supply models that are incompletely specified. The specificity of the test is that one model is always true by construction (the true model is hypothesized by the null unless outperformed by the alternative). To perform the test we now project the recovered marginal costs on manufacturer and retailer cost components via GMM estimation procedure and obtain the Cox-type statistic values for all pairs of scenarios. After normalizing and standardizing these values we then obtain their respective p-values from the standard normal distribution. (table 7). Table 7 reports the p-values of the GMM test statistic for the demand models with constant marginal utility. The rows present the supply models under the null hypothesis, and the columns present the competing alternatives. At 10 % level of significance it is evident that the nonlinear model with manufacturers engaged in perfect competition with retailers being the only profit maximizers (3.1) provides the best match to data on manufacturer and retailer costs. This is because the model 3.1 outperforms the remaining scenarios, in the meatime surviving against all the alternative. For comparison, Villas-Boas (2007) also finds this supply scenario superior to the rest of models under study.

Conclusions

This manuscript studies the market conduct of milk manufacturers and retail chains in a Midwestern state in the United States. It utilizes cross-sectional and time series variation in market-level milk data and annual variation in consumer demographics to estimate structural parameters of random coefficient demand model, and navigates through several models of vertical interactions on the supply side for the best match with manufacturer and retailer cost data.

Results show that demand model with underlying constant marginal costs supports a supply scenario with retailers being the only decision makers and manufacturers following marginal cost pricing rule. Later they may collect a part or full rents from the retailers through two-part tariffs. The findings of this study are important in the light of increased interest in market conduct of players in milk supply chain on the part of the U.S. Department of Justice and the U.S. Department of Agriculture.

Literature

Berge's-Sennou, F. 2006. "Store Loyalty, Bargaining Power and the Private Label Production Issue", *European Review of Agricultural Economics,* 33(3): 315-335.

Berry, S., J.Levinsohn and A.Pakes, 1995. "Automobile Prices in Market Equilibrium", *Econometrica*, 63(4): .841-890.

Bhat, C., 1999. "Quasi-Random Maximum Simulated Likelihood Estimation of the Mixed Multinomial Logit Model", working paper, Department of Civil Engineering, University of Texas, Austin.

Bresnahan, T., 1989. "Empirical Studies of Industries with Market Power", Schmalensee, R., R. D. Willig eds., Handbook of Industrial Organization, Volume II, Amsterdam: North Holland: 1011-1057.

Goldberg, P.K and F. Verboven, 2001. "The Evolution of Price Dispersion in European Car Markets", *Review of Economic Studies*: 811-848.

Nakamura, E. and D. Zerom, 2010. "Accounting for Incomplete Pass-Through", *Review of Economic Studies*, 77: 1192-1230.

Nevo, A., 2000. "A Practitioner's Guide to Estimation of Random Coefficients Logit Models of Demand", *Journal of Economics & Management Strategy*, 9(4): 513-548.

Nevo, A., 2001. "Measuring Market Power in the Ready-To-Eat Cereal Industry", *Econometrica*, 69(2): 307-342.

Schmalensee, R., 1981. "Monopolistic Two-Part Pricing Arrangements", *RAND Journal of Economics*, 12(2): 445-466.

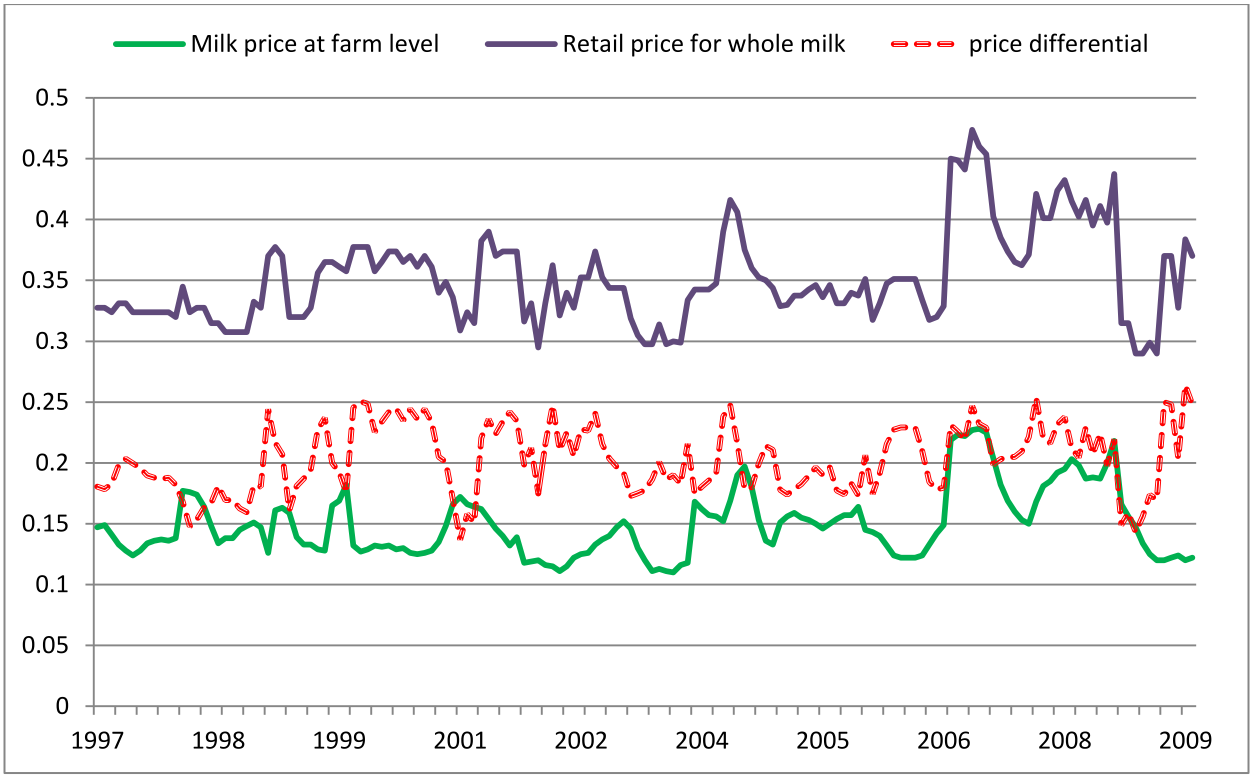
The U.S. Food Marketing System: Recent Developments, 1997-2006, by Steve W. Martinez, ERR-42, USDA, Economic Research Service, May 2007.

Villas-Boas, S.B., 2007. "Vertical Contracts between Manufacturers and Retailers: Inference with Limited Data", *Review of Economic Studies*, 74(2): 625–652.

R. J. Volpe III and Nathalie Lavoie, 2008. "The Effect of Wal-Mart Supercenters on Grocery Prices in New England", *Review of Agricultural Economics*, 30 (1): 4-26.

Von Cramon-Taubebel, S. (1998). "Estimating asymmetric price transmission with the error correction representation: An application to the German pork market", *European Review of Agricultural Economics*, 25(1): 1-18.

Figure 1 Farm level and retail prices of whole milk in a major city in a Midwestern state



Note: Prices are $ U.S. per cwt. of milk.

Table 1 Products defined as combinations of manufacturer-retailer-milk fat

Product	*Manufacturer*	*Retail Chain*	*Fat Content*	*# of 4-Weeks*	*Not in Months*
1	Bareman's Dairy	2	Skim	78	
2	Bareman's Dairy	2	Reduced	78	
3	Bareman's Dairy	2	Whole	78	
4	Dean Foods Co	1	Skim	78	
5	Dean Foods Co	3	Skim	78	
6	Dean Foods Co	1	Low	53	27-51,
7	Dean Foods Co	1	Reduced	78	
8	Dean Foods Co	3	Reduced	78	
9	Dean Foods Co	1	Whole	78	
10	Dean Foods Co	3	Whole	78	
11	J&J	1	Skim	78	
12	J&J	3	Skim	78	
13	J&J	1	Low	41	18,19,42-51
14	J&J	1	Reduced	78	
15	J&J	3	Reduced	78	
16	J&J	1	Whole	66	2-11,15,17
17	J&J	3	Whole	78	
18	Private Label	1	Skim	71	1-7,
19	Private Label	3	Skim	78	
20	Private Label	3	Low	78	
21	Private Label	1	Reduced	71	1-7,
22	Private Label	3	Reduced	78	
23	Private Label	1	Whole	71	1-7,
24	Private Label	3	Whole	78	
25	Organic Valley	1	Skim	65	1-5, 71-78
26	Organic Valley	1	Low	63	1-7, 71-78
27	Organic Valley	1	Reduced	65	1-5, 71-78
28	Organic Valley	1	Whole	65	1-5, 71-78
29	Bareman's Dairy	2	Skim	78	
30	Bareman's Dairy	2	Reduced	78	
31	Bareman's Dairy	2	Whole	78	
32	Dean Foods Co	3	Skim	78	
33	Dean Foods Co	6	Skim	78	
34	Dean Foods Co	6	Low	78	
35	Dean Foods Co	3	Reduced	78	
36	Dean Foods Co	6	Reduced	78	
37	Dean Foods Co	3	Whole	78	
38	Dean Foods Co	6	Whole	78	
39	J&J	3	Skim	78	
40	J&J	6	Skim	78	

41	J&J	3	Low	42	45-69,71-78
42	J&J	6	Low	78	
43	J&J	3	Reduced	78	
44	J&J	6	Reduced	78	
45	J&J	3	Whole	78	
46	J&J	6	Whole	63	1.0-15
47	Private Label	2	Skim	43	1.0-35
48	Private Label	3	Skim	78	
49	Private Label	6	Skim	78	
50	Private Label	3	Low	78	
51	Private Label	6	Low	78	
52	Private Label	2	Reduced	43	1.0-35
53	Private Label	3	Reduced	78	
54	Private Label	6	Reduced	78	
55	Private Label	2	Whole	43	1.0-35
56	Private Label	3	Whole	78	
57	Private Label	6	Whole	78	

Table 2 Descriptive Statistics of Price, Container Size, and Market Share

	Mean	S. D.	Min	Max
Price (cents/half a pint)	29.372	14.731	10.486	56.810
Product share across markets (%)	1.468	2.741	0.001	14.238
Aggregate product share (%)	38.946	7.557	21.745	52.214
Average container size (pints)	5.004	1.738	1.128	8.000
Mean of aggregate retailer shares in each market (%)				
Retailer 1		10.807		
Retailer 2		0.243		
Retailer 3		26.449		
Retailer 4		13.701		
Mean of aggregate manufacturer shares in each market (%)				
A local milk processor			0.182	
Dean's Food			2.415	
Johnson & Johnson			0.251	
Private Labels			36.082	
Organic Valley			0.032	

Table 3 Results from the Multinomial Logit Demand

	Logit			IV Logit		
Variable	(a)	(b)	(c)	(a)	(b)	(c)
Price	-8.440	-8.439	-8.758	-8.713	-8.712	-8.998
	0.215	*0.215*	*0.205*	*0.251*	*0.251*	*0.242*
Milkfat		-0.196	-1.077		-0.191	-1.297
		0.009	*0.043*		*0.010*	*0.051*
Mean(Income($ US)/Family size)			1.297			1.379
			0.086			*0.108*
Mean(Household head's age)			0.535			0.857
			0.069			*0.098*
Mean(Number of children < 18)			1.749			1.820
			0.097			*0.106*
R	0.940	0.940	0.946			
F statistic: Cost coefficients=0						

Note: The dependent variable in each regression is the difference between the log of actual market shares and that of the outside good.

Table 4 Results from the Random Coefficient Logit Demand Model

Variable	Means β	Unobserved Demo σ	HH Income/Family size	HH head's Age	# of Child <18
Price	**-17.820*****	0.096	0.161	**3.363*****	**-5.394*****
	0.410	*0.174*	*0.248*	*0.190*	*0.390*
Constant	**-11.474**$_{\mathbf{a}}^{***}$	**0.369*****	**2.010*****	**0.286*****	**3.505*****
	0.137	*0.086*	*0.200*	*0.037*	*0.179*
Fat content	**0.083**$_{\mathbf{a}}^{***}$	**0.620*****	**-0.646***	-0.117	**-0.867*****
	0.003	*0.052*	*0.333*	*0.141*	*0.232*
GMM objective			747.270		
χ^2 stat			6.14E+04		
Price coef.>0			0.017%		

*Note: GMM estimates are obtained based on 4139 observations. Bold identifies the estimates that are statistically significant at 1 % significance level. Standard errors are in italic. *Estimates are obtained via minimum distance procedure.*

Figure 2

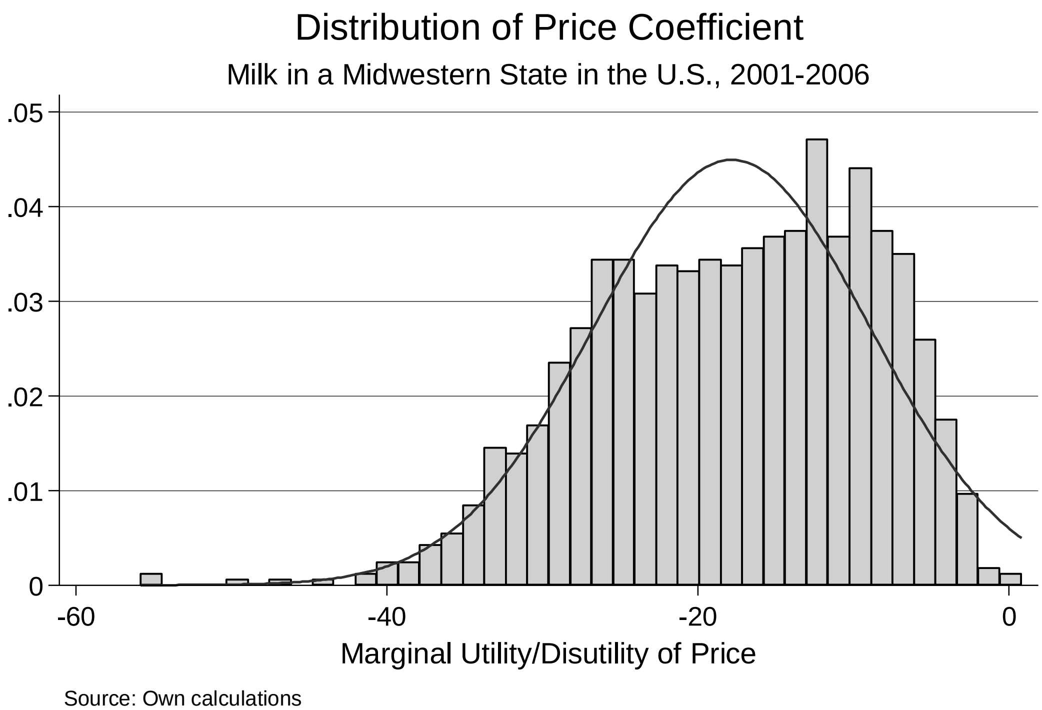

Distribution of Price Coefficient
Milk in a Midwestern State in the U.S., 2001-2006
.05
.04
.03
.02
.01
0
-60
-40
-20
0
Marginal Utility/Disutility of Price
Source: Own calculations

Figure 3

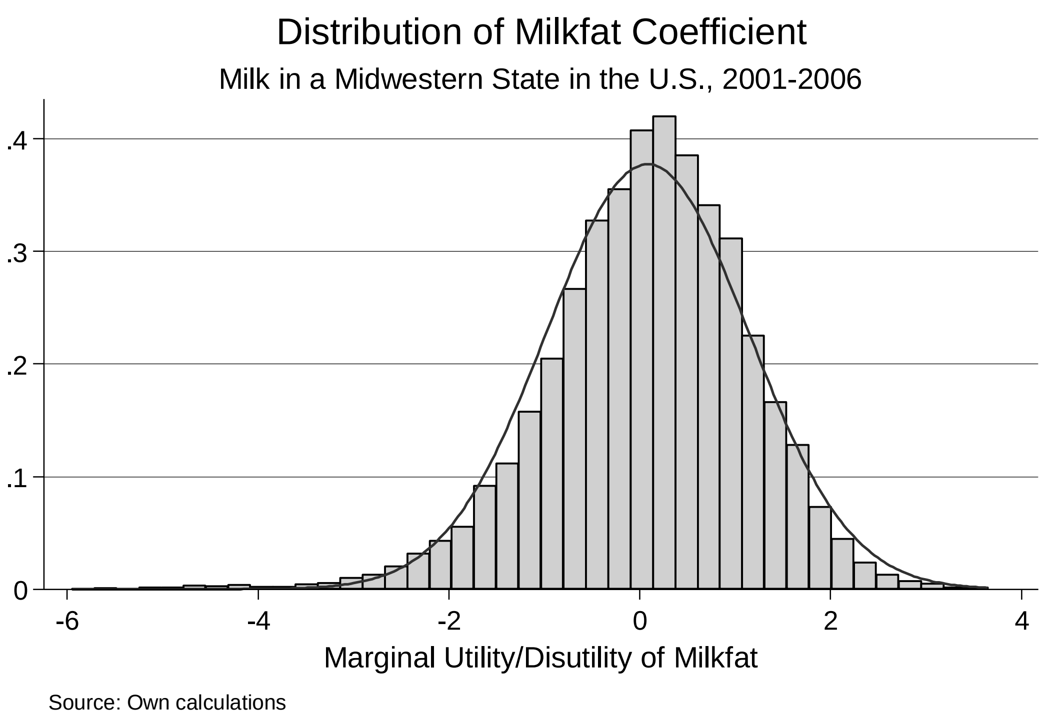


Figure 4

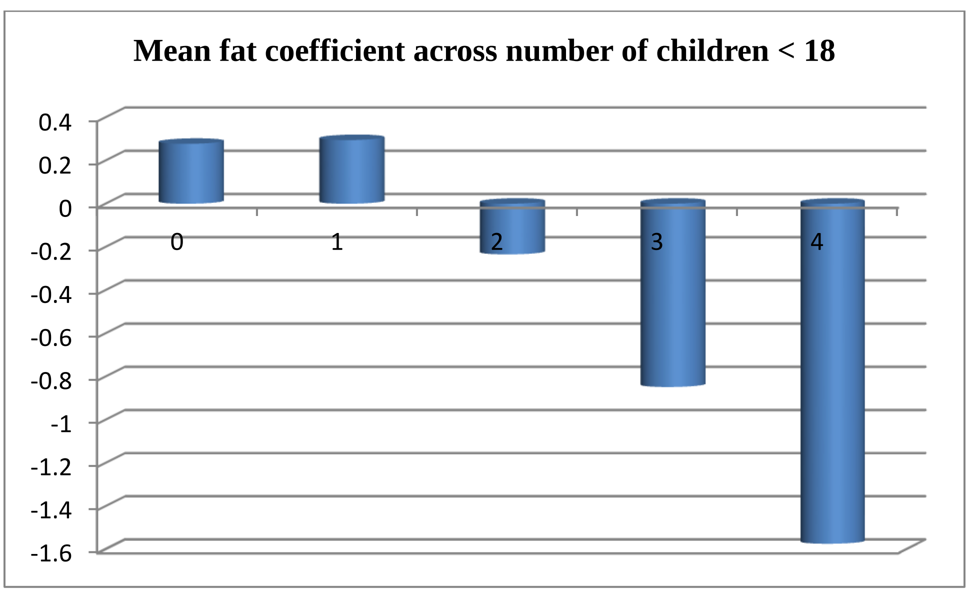


Table 5 Mean elasticity estimates for logit and random coefficient demand models

	Logit model		Random coefficients model		
	Own price	Cross price	Own price	Cross price	
				Mean	St. Dev.
Manufacturer					
Local	-1.368	0.001	-2.787	0.059	0.114
Dean	-3.101	0.005	-2.799	0.032	0.056
J&J	-4.079	0.001	-2.886	0.022	0.035
Private label	-1.169	0.049	-2.440	0.056	0.115
Organic Valley	-3.993	0.000	-2.988	0.022	0.035
Retailer chain					
Chain 1	-2.995	0.010	-2.996	0.038	0.073
Chain 2	-1.295	0.001	-2.603	0.058	0.111
Chain 3	-2.765	0.030	-2.652	0.036	0.069
Chain 4	-2.931	0.016	-2.585	0.031	0.056
Average all	-2.628	0.017	-2.721	0.039	0.074

Table 6 Vertical Lerner Index across the supply scenarios (%)

Supply scenario	Medium	S.D.	Min	Max
1. Double marginalization	54.9	7.1	43.7	64.7
2. Hybrid model	57.0	3.7	49.0	62.2
3.1. Retailer as residual claimant	45.1	3.6	38.5	51.5
3.2. Manuf. as residual claimant	41.7	4.2	35.3	62.0
4. Manufacturer collusion	33.3	27.9	-43.6	66.0
5. Retail collusion	83.1	6.9	70.8	109.8
6. Monopoly	84.9	11.4	69.8	110.7

Table 7 Pairwise non-nested test for supply scenarios estimated by GMM

	Competing alternative models						
Model under null hypothesis	1	2	3.1	3.2	4	5	6
1. Double marginalization		0.46	0.07	0.30	0.39	0.15	0.13
2. Hybrid	0.45		0.07	0.30	0.38	0.15	0.12
3.1. No wholesale margin	0.43	0.41		0.12	0.20	0.13	0.10
3.2. No retailer margin	0.48	0.50	0.05		0.34	0.17	0.14
4. Manufacturer collusion	0.47	0.48	0.06	0.27		0.16	0.14
5. Retailer collusion	0.36	0.38	0.06	0.33	0.43		0.07
6. Vertical monopoly	0.35	0.37	0.06	0.34	0.44	0.08	

Notes: These are p-values from pairwise Cox-type statistics as proposed by Smith, 1992. The models under null hypothesis are provided in the row, and the alternative models are in columns.

Source: Own calculations.