Vertical Channel Analysis of the U.S. Milk Market

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Abstract

The objective of the research in this study is to evaluate the pricing and market conduct of milk manufacturers and retailers. Using data from a U.S. Midwestern state, we estimate a random coefficient logit demand model (RCL) to empirically investigate a range of possible scenarios in the milk supply chain. These include vertical leader-follower model with underlying Bertrand-Nash pricing, models allowing for nonlinear pricing contracts, and collusion scenarios at various levels in the supply chain. This study contributes to the literature in the following ways. First, it generalizes the RCL demand model via Box-Cox power transformation. While previous studies rely on ad hoc specified linear indirect utility, this procedure allows data to determine the functional form of utility. Power transformation parameters cannot be obtained analytically with product-level data, given that consumer choices are unobserved. We propose an algorithm to estimate the transformation and consumer heterogeneous taste parameters sequentially. The model is identified using annual variation in consumer demographics along with cross-sectional and time series variation in milk consumption. Finally, the milk choice set is allowed to vary across markets. It should be mentioned that jointly estimating the manufacturing sector, the vertical channel, and the retail sector will more likely yield reliable estimates of structural parameters vis-à-vis studies investigating food supply chain sectors in isolation.

Several key results are obtained from the research. First, the estimate of demand “superelasticity”suggests that retailers have incentives to adjust retail markups to enhance their market power. Next, supply selection bias associated with imposing restriction on the demand-side framework is shown to have formidable policy implications. Namely, empirical results from the general demand show that retailers are more powerful than they would appear otherwise. In the face of high concentration and a small presence of Wall-Mart in these markets this seems a plausible scenario.

Key words: Market conduct, random coefficient logit, vertical chain, Box-Cox power transformation

1. Introduction

Rising concentration in U.S. food retailing has the potential to reshape not only the competitive landscape in final goods, but also vertical interactions between retailers and manufacturers and horizontal interactions among manufacturers. This in turn has important welfare implications for both producers and consumers of food. When an industry evolves toward greater concentration, it usually occurs because firms either seek market power that confers higher output prices or lower input prices on its buyers or sellers, or the firm actively seeks scale or scope economies that lead to more efficient welfare outcomes. When two vertically aligned industries are concentrated, the vertical channel relating the two can become complicated. For example, if one large retailer is able to use its buying power to reduce its costs, the ability of the manufacturing sector to react may mean it will try to lower its own input procurement costs or perhaps it will try to raise its selling price to other retailers. In another extreme, a handful of manufacturers may own some of the retail outlets (in gasoline markets) with important decisions on vertical interactions and strategic variables being made at manufacturer-level. In this vertical setup, the vertically integrated manufacturers may also have the incentive to charge higher prices to their non-integrated rivals in downstream markets (Hastings, 2004; Hastings and Gilbert, 2005). Therefore, studies that abstract from potential vertical considerations in accounting for market behavior of participants in the supply chain will result in unreliable outcomes and policy implications.

The primary objective of this study is to empirically analyze the U.S. milk marketing chain with a major emphasis on interactions between milk manufacturers and major retail chains. There has been a growing interest in milk markets recently[1], motivated in part by an interesting

[1] This is exemplified by a recent interest on the part of the USDA and DOJ to better understand the competitive structure of milk markets throughout the nation.

dynamics in milk prices at various levels of milk supply chain. Specifically, in many cases farm level milk prices manifested substantial volatility with prices in downstream markets not necessarily following the respective ups and downs. Moreover, although raw milk price constitutes an important share of the retail-level price, plummeting farm prices in certain periods have gone in parallel with relatively stable prices in the downstream channels. This may be suggestive of major retail chains exercising market power against the upstream participants. In theory, retailers draw market power not only from increasing retail concentration in the recent years, but also strategic use of well-established private label products (PL). The specificity of PL products (immunity to intra and inter-brand competition) makes retailers flexible in their dealing against rivals on the horizontal landscape, while enhancing their bargaining power vertically (Steiner, 2004).

Our empirical investigation of implications of structural changes for milk supply chain is based on analysis of a U.S. Midwestern state. This constitutes a rather concentrated market at the retail level[2] with a handful of large manufacturers accounting for a major share of milk products; therefore, we employ vertical oligopolistic models to study its dynamics using product-level data from the Information Resources Incorporated (IRI). In spite of many research studies exploring the U.S. milk market, only a few make use of recent methodological developments in supply and demand analysis to evaluate the market behavior of the supply chain participants (see for example Lopez and Lopez, 2009; Richards et al., 2010). This would make possible not only brand level analysis that builds upon realistic consumer substitution patterns, but would also allow obtaining direct estimates of market behavior of economic agents in question.

[2] Three major retail chains collectively account for more than 70 % of the total market share in these markets. In addition, we observe the same chains for the entire period of the study, which allows for tracking their behavior over time.

Milk demand is modeled via a random coefficient logit specification (RCL) (Berry, Levinsohn, and Pakes (BLP), 1995; Nevo, 2001; Nakamura and Zerom, 2010; Bonnet and Dubois, 2009; 2010) taking into account vertical interactions of milk manufacturers and major retail chains. Following a menu approach (Bresnahan, 1987; Gasmi et al., 1992), we then use the demand estimates to navigate through several supply scenarios that include vertical leader-follower model with underlying Bertrand-Nash pricing, models allowing for nonlinear pricing contracts, and collusion scenarios at various levels in the supply chain. This study extends a seminal work by Villas-Boas (2007) that allows obtaining market conduct estimates for milk manufacturers and retailers without having access to wholesale-level milk prices. Previous studies, on the other hand, relied to a major extent on a conjectural variation approach in the spirit of Newly Empirical Industrial Organization (NEIO)[3] to explore the competitive nature in an industry or across several industries at a retail level (see for example, Hyde and Perloff, 1998), or in a vertical context (for example, Kadiyali et al., 2002; Chintagunta et al., 2002). While the conjectural variation framework gives an idea of where markets stand in relation to perfect competition or monopoly (values of conjectural variation parameter lying between the two extreme scenarios are not interpretable), the novelty of the above approach is that it allows obtaining a direct estimate of market conduct and pricing behavior (as measured by a Lerner Index (LI) of price over marginal cost markup).

Our choice of a random utility discrete choice framework for modeling milk demand is justified by its flexibility in handling a potentially large number of products. This is because milk demand is projected on various attributes of milk unlike neoclassical demand systems.[4]

[3] An exception is a study by Sudhir (2001), which explores manufacturer behavior in a vertical context allowing a strategic retailer in the market.
[4] Almost Ideal Demand Systems of Deaton and Muellbauer (1980), for example, are plagued with the curse of dimensionality, as the budget share equations are functions of prices of products in the system.

Moreover, modeling somewhat realistic substitution patterns is crucial for the economic effects, which underlie the estimates of market power. This fact substantiates the choice of an RCL demand; which allows consumers to have correlated choices across products offered in each market (substitution pattern is allowed to be a function of consumer demographics and milk attributes).

This study contributes to the literature in the following important ways. First and foremost, it generalizes the RCL demand specification while the contributions of all known previous studies focus on the supply side (see for example Villas-Boas, 2007; Nakamura and Zerom, 2010; Bonnet and Dubois, 2010). Specifically, instead of specifying an ad hoc linear indirect utility function, we allow the data to determine the functional form of the indirect utility. As a result, the indirect utility may take any form between logarithmic and linear functional specifications. To do so, we power transform the indirect utility function via Box-Cox procedure that allows modeling potential diminishing marginal utility of milk attributes (Box and Cox, 1964). Although the importance of generalizing demand models via power transformations cannot be underestimated, only a study by Orro et al., (2005) employs a similar framework to test across various specifications of transportation demand. However, they rely on consumer-level data; which allow obtaining estimates of power transformation parameters analytically. The current study, on the contrary, uses product-level data (actual consumer choices are unobserved to the researcher) which provide no guidance as to how power transform the demand function empirically. The importance of the major contribution of this manuscript is that it proposes a numerical algorithm to estimate power transformation and consumer heterogeneous taste parameters altogether.

Secondly, unlike previous studies, we model annual variation in consumer demographics along with cross-sectional and time series variation in milk consumption. Furthermore, the choice set for milk is allowed to vary across markets. These will likely enhance the identification power of the model and help pin down the elasticity measures underlying the market power estimates.

With the increasing prevalence of the RCL demand specification in NEIO studies, the supply model selection bias may well have a formidable impact on policy implications. More specifically, the results support a conjecture that major retail chains are more powerful than they would appear under the less general model of demand. Given the concentration level of this market and the small presence of Wall-Mart (less than 5 % of total market share), this seems a plausible scenario. The findings from similar studies (for example Villas-Boas, 2007; Bonnet and Dubois, 2010) suggest that retailers have, indeed, reshaped the vertical competitive landscape to their advantage. Furthermore, Steiner (2004) provides a careful discussion of possible factors behind this reality.

The remainder of this manuscript proceeds as follows. The next section presents the basic RCL demand model and the power transformation technique, along with several models of interaction among the downstream players. Section three presents estimation details of the basic demand, and the numerical algorithm for estimating the generalized demand specification. Section four briefly discusses the market-level data used in this study. Empirical results follow immediately. The final section concludes and provides some suggestions for future work.

2. Methodology

To model the demand for milk we rely upon an RCL specification (Berry, Levinsohn and Pakes, 1995; Nevo, 2001; Nakamura and Zerom, 2010) that is flexible enough to approximate any random utility model (McFadden and Train, 2000). More precisely, we generalize the RCL demand via Box-Cox power transformation; which allows the underlying indirect utility function to range from a linear to a logarithmic form (Box and Cox, 1964; Orro et al., 2005). Using two-step procedure (Goldberg and Verboven, 2001) we then take the demand estimates to several models of interactions among downstream players in milk supply chain that extend from Stackelberg in Bertrand-Nash to a vertical monopoly. Given the non-nested nature of supply scenarios considered here a relevant testing procedure by Rivers and Vuong (2002) is performed next with the aim of determining the vertical competitive atmosphere in milk markets.

2.1. Basic demand specification

Milk demand is modeled using a discrete choice framework where consumers are assumed to make a choice from (N + 1) alternatives comprised of N products and an outside option (no purchase at all or purchase at other outlets excluded from this study). Products are defined as unique combinations of milk manufacturers, major retail chains operating in respective markets, and the fat content of milk. Furthermore, we assume that consumers have a quasi-linear utility function (income effects are absent) with a corresponding indirect utility specified as:

$$U_{ijt} = \begin{cases} x_{jt}\beta_i - p_{jt}\alpha_i + \xi_{jt} + \varepsilon_{ijt} & \text{if} \quad c_j \neq 0 \\ \varepsilon_{i0t} & \text{otherwise} \end{cases} \tag{1}$$

where U_{ijt} is the indirect utility that consumer i derives from choice j in market $t = 1, 2, \dots, T$, x_{jt} represents the observed product characteristics other than milk price (such as the milk fat content, organic, lactose free), p_{jt} is the price of j^{th} milk in market t, ξ_{jt} embeds unobserved (by the researcher) milk characteristics also known as milk quality, ε_{ijt} represents attributes unobservable by the consumer, and $c_j = \{0,1\}$ denotes a purchase of milk from the choice set at value 1, and outside option otherwise. For reasons mentioned below, ε_{ijt} is assumed to be mean zero, and distributed independently and identically according to a type I Extreme Value distribution.

Consumer taste heterogeneity is allowed to incorporate systematic, as well as random taste variation (Train, 2003) as follows:

$$\begin{pmatrix} \beta_i \\ \alpha_i \end{pmatrix} = \begin{pmatrix} \beta \\ \alpha \end{pmatrix} + \Psi D_i + \Lambda \Theta_i, \ \forall \ i = 1, 2, \ldots, I \qquad (2)$$

where α and β are the mean population parameters of the marginal utility/disutility of price and other product attributes modeled, D_i and Θ_i are observed and unobserved consumer demographics (normally assumed to follow a standard normal distribution), respectively, Ψ and Λ measure heterogeneity in consumer tastes. This allows the choice set in a given market to be meaningfully correlated for each consumer; which results in realistic substitution patterns. This feature of the RCL models cannot be underestimated in the empirical IO, where the economic effects play a key role in obtaining market power estimates.

With the usual assumption of purchase of a product unit j that yields the highest utility for a given choice set in the market t, one obtains the respective probability for individual i as given by:[5]

$$P_{ijt} = e^{x_{jt}\beta_i - p_{jt}\alpha_i + \xi_{jt}} \Big/ \left(1 + \sum_{m=1}^{N} e^{x_{mt}\beta_i - p_{mt}\alpha_i + \xi_{mt}}\right) \qquad (3)$$

The predicted demand for milk j in market t is then computed by aggregating individual probabilities over the distribution of consumer taste heterogeneity as follows:

[5] The analytical formula for purchase probability is obtained by virtue of the distributional assumptions on ε_{ijt}.

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

Finally, we use the following formulas to estimate the own and cross price elasticity measures:

$$\eta_{jkt} = \frac{\partial s_{jt}}{\partial p_{kt}} \frac{p_{kt}}{s_{jt}} = \begin{cases} -\dfrac{p_{jt}}{s_{jt}} \iint \alpha_i s_{ijt}(1-s_{ijt})\, dF_1(D)\, dF_2(Z) & \text{if } k=j \\ \dfrac{p_{kt}}{s_{jt}} \iint \alpha_i s_{ijt} s_{ikt}\, dF_1(D)\, dF_2(Z) & \text{otherwise} \end{cases} \qquad (5)$$

2.2. General demand specification

The choice of the linear indirect utility function underlying the basic RCL demand specification is clearly ad hoc. Furthermore, its functional form is restrictive in that it implies constant marginal utility of product attributes. More specifically, any change in the milk fat value affects the milk choice probabilities independently of the initial level of milk consumed. This seems restrictive in the light of increasing health consciousness in the U.S., where one would expect consumers deriving lower marginal utility from incremental milk consumption (see Gaudry (2010) for a thorough discussion of constant marginal utility assumption).

We generalize the RCL demand by allowing the data to determine the functional form of the indirect utility (Gaudry and Willis, 1978). To do so, we power transform indirect utility via Box-Cox procedure allowing it to embrace a range of functional forms extending from logarithmic to linear (Blayac, 2003; Orro et al., 2005). Thus, if the linear formulation is outperformed by competing alternatives then empirical evidence supports diminishing marginal utility.

The Box-Cox power transformation can be applied to some or all of the product characteristics that accept strictly positive values as follows (Box and Cox, 1964; Train, 2003):

$$U_{ijt} = x_{jt}^{(\lambda_{jt})} \beta_i - p_{jt} \alpha_i + \xi_{jt} + \varepsilon_{ijt} \tag{6}$$

Where

$$x^{(\lambda)} = \begin{cases} \dfrac{x^{\lambda} - 1}{\lambda} & \text{if } \lambda \neq 0 \\ \log(x) & \text{otherwise} \end{cases} \tag{7}$$

Exponential parameters λ_{jt} can be specified to be the same for all product attributes, or in a more general setting they would vary across product characteristics. These parameters need to be estimated along with consumer heterogeneous taste parameters; however, unlike in studies that rely upon observed consumer behavior (for example Orro et al., 2005), market-level data do not allow obtaining them analytically. Therefore, we propose a numerical algorithm to estimate the demand parameters simultaneously by means of three levels of sequential optimization.

2.3. Supply Models

Supply scenarios considered in this study range from Stackelberg in Bertrand-Nash to vertical monopoly between milk manufacturers and major retail chains (Villas-Boas, 2007; Bonnet and Dubois, 2010). While not exhaustive, these should provide a fairly broad coverage of vertical interactions in the downstream channels of milk marketing system.

2.3.1 Stackelberg in Bertrand-Nash (double marginalization)

This is a simple linear pricing scenario with a handful of Nash-Bertrand milk manufacturers and retail chains engaged in oligopolistic competition, moreover, manufacturers make the first move. Given this structure of a game, equilibrium prices are solved for via backward induction where retailer optimality conditions are obtained first.

The retailer e in market t is characterized by the following profit function

$$\pi_{et} = \sum_{i \in I_{et}} \left(p_{it} - p_{it}^{w} - c_{it}^{e} \right) s_{it}(p) \tag{8}$$

Where I_{et} represents product offerings by retailer e in market t, p_{it}^{w} is the wholesale price of product i, c_{it}^{e} is the marginal cost of producing i by retailer e, and $s_{it}(p)$ is the i^{th} product's market share in market t. The pure strategy equilibrium Bertrand-Nash prices then can be obtained by differentiating (8) with respect to respective retail-level prices as follows:

$$s_{it} + \sum_{k \in I_{et}} \left(p_{kt} - p_{kt}^{w} - c_{kt}^{e} \right) \partial s_{kt} / \partial p_{it} = 0 \qquad \forall i \in I_{et}, \quad \text{for } e = 1, \dots, n_e \tag{9}$$

Where n_e is the number of active retail chains in market t. Stacking together optimality conditions for all products in I_{et}, one can obtain price over marginal cost markup for retailer e in market t as specified below:

$$\underbrace{p_t - p_t^{w} - c_t^{e}}_{\omega_t} = -\left(O_e * \Delta_{et} \right)^{-1} s_t(p) \qquad \text{for } e = 1, \dots, n_e \tag{10}$$

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

By the same token, taking retailer optimality conditions as given, manufacturer markups can be obtained as follows:

$$\underbrace{p_t^{w} - c_t^{w}}_{\tau_t} = -\left(O_w * \Delta_{wt} \right)^{-1} s_t(p) \qquad \text{for } w = 1, \dots, m_w \tag{11}$$

where m_w is the number of milk manufacturers supplying to market t, c_t^{w} is a vector of marginal costs incurred by manufacturer w, O_w displays its ownership structure, and $\Delta_{wt}(p(w))$ is a matrix reflecting manufacturer's response to variations in retail prices:

$$\partial s_{kt}(p(w)) / \partial p_{kt}^{w} = (\partial s_{kt} / \partial p_{kt})(\partial p_{kt} / \partial p_{kt}^{w}) \tag{12}$$

Sensitivity of manufacturer prices to changes in retail prices, represented by $\partial p_{kt} / \partial p_{kt}^{w}$, is generally unknown in practical applications, given the fact that manufacturer/wholesale level prices are rarely observed. Therefore, it is imperative to express the response matrix solely in terms of observables (retail prices, actual market shares, and ownership structure). To do so, we totally differentiate the j^{th} equation in (9) with respect to retailer prices dp_k, $k=1,\ldots,n$ and a wholesale price p_m^w with variation dp_m^w:

$$\sum_{k=1} \underbrace{\left(\frac{\partial s_j}{\partial p_k} + \sum_i \left[O_e(i,j)(p_i - p_i^w - c_i^e) \frac{\partial^2 s_i}{\partial p_j \partial p_k} \right] + O_e(k,j) \frac{\partial s_k}{\partial p_j} \right)}_{g(j,k)} dp_k - \underbrace{O_e(m,j) \frac{\partial s_m}{\partial p_j}}_{h(j,m)} dp_m^w = 0 \qquad (13)$$

Applying the above procedure to each optimality condition in (9) and stacking together their respective relationships as in (13), we obtain $G\,dp - H_m\,dp_m^w = 0$, where G is a matrix with elements g (j, k), and H_m is a vector of dimension n with elements h (j, m). The m^{th} column of manufacturer sensitivity matrix is then given by $dp/dp_m^w = G^{-1}H_m$, combining all n columns of which yield the full sensitivity matrix as $\Delta_p = G^{-1}H$. Manufacturer response matrix is then simply $\Delta_w = \Delta_p^{'} \Delta_e$, the substitution of which into (11) yields the implied markups for manufacturers.

2.3.2 Hybrid model

The only difference between the hybrid and Stackelberg Bertrand-Nash models is that retail chains own private label milk. Under this ownership structure retailers eliminate manufacturer markup for private labels which puts some competitive pressure on national brand milk. Retail markups, therefore, remain unchanged as in (10), while manufacturer markups are expectedly lower than in (11) as provided below:

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

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

2.3.3 Nonlinear pricing models

Two alternative nonlinear pricing models considered here allow for perfectly competitive manufacturers with retailers being the only profit maximizing channel (manufacturers may later extract a part or full retail rents via two-part tariffs), and vice versa. This is because identification of markups for downstream two channels when they compete imperfectly in a nonlinear pricing context is a major issue (Bonnet et al., 2009).

With perfectly competitive manufacturers, they obtain zero markups, while retail markups are:

$$p_t - c_t^e - c_t^w = -\left(O_e * \Delta_{et}\right)^{-1} s_t(p) \tag{15}$$

In the second sub-scenario, retailers receive zero markups, and manufacturers claim the vertical markup for each product they offer:

$$p_t - c_t^e - c_t^w = -\left(O_w * \Delta_{et}\right)^{-1} s_t(p) \tag{16}$$

Exploring possible mechanisms according to which the downstream channels redistribute their profits may be an interesting area of study, which is not pursued here.

2.3.4 Collusion at manufacturer level

This scenario assumes that manufacturers maximize their joint profit, with retailers still pursuing their individual interests. This results in retailers receiving the same markup as in

Stackelberg Nash-Bertrand provided by (10). Manufacturers' markups, on the other hand, is given by (11), with the only difference being in the manufacturer ownership matrix, which is now full of ones.

2.3.5 Collusion at retailer level

By symmetry, markups accruing to manufacturers are specified by (11), and those for retailers are as in (10), provided that retailer ownership matrix is all ones.

2.3.6 Vertical collusion / monopoly

In this extreme scenario manufacturers and retail chains act as one enterprise maximizing joint profit. In other terms, they come together to extract monopoly rents given by:

$$p_t - c_t^e - c_t^w = -\left(O_1 * \Delta_{et}\right)^{-1} s_t(p) \tag{17}$$

2.4. Testing Procedure

Given the non nested nature of the supply models in question, we perform a non-nested testing procedure to infer on the nature of competition in downstream channels. For that purpose we first estimate manufacturer (ω_{jt}) and retailer (τ_{jt}) markups for the supply scenarios considered, and obtain implied vertical marginal costs (sum of milk production and marketing related marginal costs) for the respective supply models as follows:

$$mc_{it} = p_{it} - (\omega_{it} + \tau_{it}) \tag{18}$$

Statistical inference is then based upon pair-wise comparisons of marginal cost functions from various supply models:

$$\begin{cases} mc_{it}^A = f\left(c_{i1t}^A, \ldots, c_{i\psi t}^A\right) + \iota_{it}^A \\ mc_{it}^B = f\left(c_{i1t}^B, \ldots, c_{i\psi t}^B\right) + \iota_{it}^B \end{cases} \tag{19}$$

Where A and B denote the null and alternative hypothesis, $c_{i1t}, ..., c_{i\psi t}$ represent stochastic cost shocks observed by the researcher, f is a total marginal cost function assumed to be additively separable in manufacturer and retailer-level cost components, and ι_{it} is an unobservable random shock to the cost.

Non nested test procedure proposed by Rivers and Vuong (2002) is then conducted to infer on the nature of downstream competition in milk markets. This provides a very general testing framework since the stochastic marginal cost functions (19) are allowed to be incompletely specified; moreover, neither specification is assumed to be true under the null hypothesis (unlike a Cox-type test developed by Smith (1992) for models estimated via GMM). The test statistic measures the distance between the lack-of-fit criteria from the competing stochastic marginal cost functions that are estimated via NLS or GMM, with the identifying assumption that observed cost shocks $c_{i1t}, ..., c_{i\psi t}$ are orthogonal to the unobserved shock ι_{it} (Rivers and Vuong, 2002; Bonnet and Dubois, 2009; 2010). The test statistic is provided below:

$$R_T = \frac{\sqrt{T}}{\hat{\sigma}_T}\left(\hat{\Upsilon}_t^A(\hat{\theta}_3^A) - \hat{\Upsilon}_t^B(\hat{\theta}_3^B)\right)$$

where $\hat{\Upsilon}_t^A(\,)$, $\hat{\Upsilon}_t^B(\,)$ are minimands employed in the estimation of competing marginal cost functions evaluated at the optimal values of cost parameters from the respective models (i.e., $\hat{\theta}_3^A, \hat{\theta}_3^B$), and $\hat{\sigma}_T$ represents a consistent estimator of the limiting variance of difference between the lack-of-fit criteria normalized by $\sqrt{T}$. Under some regularity conditions Rivers and Vuong show that R_T has a standard normal distribution. A given pair of models is assumed to be asymptotically equivalent under the null hypothesis given by:

$$H_0: \lim_{n \to \infty} \left[\hat{\Upsilon}_t^A(\hat{\theta}_3^A) - \hat{\Upsilon}_t^B(\hat{\theta}_3^B) \right] = 0$$

The alternative hypothesis maintaining that model under A outperforms B (resp. B outperforms A) are presented as:

$$H_1: \lim_{n \to \infty} \left[\hat{\Upsilon}_t^A(\hat{\theta}_3^A) - \hat{\Upsilon}_t^B(\hat{\theta}_3^B) \right] < 0 \quad , \quad H_2: \lim_{n \to \infty} \left[\hat{\Upsilon}_t^A(\hat{\theta}_3^A) - \hat{\Upsilon}_t^B(\hat{\theta}_3^B) \right] > 0$$

Given the non transitive nature of the tests, it should be kept in mind that no single model is assured a priori to outperform all the competing alternatives (Bonnet and Dubois, 2010).

3. Estimation

An estimable system of demand is obtained by equating the actual and predicted market shares. Estimation follows a simulated GMM procedure given that demand equations (4) can not be integrated analytically. An important issue that arises in the process is the difficulty in constructing GMM moment conditions because of nonlinear nature of demand. Specifically, the structural errors ξ_{jt} enter the demand equations in a highly nonlinear fashion, which makes it impossible to employ usual GMM techniques that are applicable in a linear world. Therefore, we rely upon a contraction mapping proposed by BLP (1995). For an expositional ease, the indirect utility in (1) is rearranged into mean utility that is common across consumers of product j (i.e., δ_{jt}), and μ_{ijt} that accounts for consumer heterogeneity.

$$U_{ijt} = \underbrace{x_{jt}\beta - p_{jt}\alpha + \xi_{jt}}_{\delta_{jt}(x_{jt}, p_{jt}, \xi_{jt}; \theta_1)} + \underbrace{[-p_{jt}, x_{jt}]\,(\Pi D_i + \Sigma v_i)}_{\mu_{ijt}(x_{jt}, p_{jt}, D_i, v_i; \theta 2)} + \varepsilon_{ijt} \tag{19}$$

Estimation algorithm obtains estimates of the linear (i.e., θ_1) and nonlinear parameters (i.e., θ_2) sequentially. For a given set of θ_2 values, it can be shown that a unique vector of ξ_{jt} equates observed and predicted shares.

$$\delta_{jt}^{h+1} = \delta_{jt}^{h} + \log s_{jt}^{a} - \log s_{jt}^{p}(\delta_{jt}^{h}, \theta_2) \quad (20)$$

$$\xi_{jt} = \delta_{jt} - (x_{jt}\beta - p_{jt}\alpha) \quad (21)$$

With the vector of structural errors ξ_{jt} at hand we then proceed to constructing moment conditions $E(\xi_{jt}|z_{jt})$ and GMM objective function as a function of θ_2 only:

$$\min_{\theta_2} \xi(\theta_2)\ Z\ \Phi^{-1} Z^{T} \xi(\theta_2) \quad (22)$$ wh

Where Z is a matrix of instrumental variables, and Φ is some weight matrix.

Price endogeneity is another issue. It stems from simultaneous determination of milk supply and demand in a structural framework. In addition, some important variables, such as advertising, specialty milk attributes (for example organic, lactose-free) are unobserved, which causes omitted variable bias. Lastly, unit prices of milk are imputed as a ratio of total amount spent to respective quantities. This reinforces price endogeneity through measurement error bias.

To account for the mean utility δ_{jt}, we use product fixed effects that capture observed and unobserved milk attributes (i.e., part of ξ_{jt} that is constant). Unobserved attributes that vary over products and markets (such as promotional activities and consumer preference changes that are not observed by the researcher, denoted by $\Delta\xi_{jt}$) are still likely to be correlated with milk prices (Nevo, 2001). Therefore, we employ instrumental variable approach to account for potential price endogeneity. Specifically, we use product fixed effects interacted with various cost components at the manufacturer and retailer level (Villas-Boas, 2007).

The addition of Box-Cox parameters to the model adds another level of difficulty to the estimation procedure. Unlike studies using consumer-level data (Orro et al., 2005), it is not possible to obtain Box-Cox parameter estimates analytically.[6] Therefore, this is the first study to propose a numerical algorithm to obtain λ estimates. More specifically, we add another loop of grid search to the basic algorithm (Nevo, 2000) to obtain the estimates of Box-Cox (λ) and consumer heterogeneous taste parameters (θ_1, θ_2) in a series of sequential optimization.

i. For each starting value of parameter λ obtain the corresponding starting values for the θ_2 parameters via basic algorithm (Nevo, 2000). This is done one at a time for each parameter in θ_2 (here 15 nonlinear parameters)

ii. Use each initial value of λ and its corresponding θ_2 parameters to obtain the estimates of θ_1 parameters, which are used in turn to estimate optimal θ_2 along with the value of GMM objective function (via basic algorithm).

iii. Repeat i-ii for all initial values of λ. One way to go about it is do a grid search, as from the economic theory $\lambda \in [0,1]$.

iv. Compare the GMM objective values computed with different sets of initial values of λ and θ_2 parameters, and choose the set with the smallest GMM objective value.

It should be mentioned that time required to run the algorithm above is not very different from that of the basic model as in Nevo, (2000), especially that we use Halton draws from the standard normal distribution (Bhat, 1999). We present some more details on this aspect of the proposed algorithm in the empirical results section.

4. Data

[6] Box-Cox parameter estimates are functions of consumer observed choices, while I do not observe individual purchase decisions

Data used in this study come from several sources. Weekly plain milk sales, average price, and milk characteristics dataset is provided by the Information Resources Incorporated (IRI). It contains market-level observations on milk sold at four large supermarket chains in two IRI city-markets in a U.S. Midwestern state from 2001 to 2006. The markets in question have been rather concentrated in the period under study. Three major retailers accounted for around 70 % of the total market share (two retailer chains operate in both markets). Particularly, the retailer 3 seems a dominant player in both IRI city-markets with an average 35 % market share (Market Scope, *Trade Dimensions,* years 2001 to 2006). Its role in the milk marketing can not be underestimated given its market share of over 52 % in the sample (table 1), while the rest of retail chains under study have relatively lower market shares (over 14 %, 11 %, and 5 % for retailers 4, 1, and 2, respectively).

An important limitation of this dataset is that only two of the three leading retail chains are covered for each IRI city in question. The market shares of the outside option in the sample (difference between the total market share and aggregate share of milks in the choice set) seem realistic in this light and compare well with those from similar studies (over 56 % and 62% in two IRI cities, respectively). Another issue is that specialty milk attributes (for example organic, lactose free) are missing for a considerable number of observations, so we do not consider them in this study but rather focus on milk fat. This attribute of milk should be an important determinant of milk consumption in the light of increasing health conscience in the U. S. recently.

Products are defined as unique combinations of milk manufacturer-retailer chain-milk fat content; which results in 57 products in the two IRI markets (table 2). Prices and quantities of milk sold are obtained by aggregating from weekly to four-week periods. We, furthermore, deflate prices from 2002 onwards using an aggregate CPI measure for urban areas. Private label milk is the cheapest option in the choice set, while lactose free milk provided by manufacturer 3 and organic milk by manufacturer 5 are relatively more expensive in the sample. To obtain the actual market shares of milk in the choice set we define the market size as a product of U.S. per capita milk consumption and the size of populations (Market Scope) in respective IRI market-cities from 2001 through 2006. Market shares simply represent the ratio of quantities of milk sold (expressed in servings, i.e. 220 ounces of milk per person in a four-week period) to the potential market demand. The share of the outside good is then the difference between the market size and the actual market shares.

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, and Class I milk price.[7] As for retailer cost components, we use the retail-level electricity prices, Federal funds effective interest rates, and retailer total sales provided in the IRI dataset. Finally, samples of demographics from the joint distribution of consumer characteristics were taken from the Current Population Survey (CPS) that is available from the U.S. Bureau of Labor. This is the first known study to allow for annual demographic variation which enhances the identifying power of the model. Overall 1200 consumers from different households were sampled in both IRI city markets. The consumer demographics include total household income, age of the household head, and the number of children less than 18 years of age.

5. Empirical Results

Results from a logit and IV logit demand models are presented in table 3. Price and milk fat coefficients are negative and statistically significant for all specifications. Results from the Hausman exogeneity test provide a strong support to the conjecture that milk price is endogenous.

[7] 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)

To control for price endogeneity, we employ a set of manufacturer and retail level cost components, which are found to be valid instruments (F-value associated with instruments is 82.2, while the critical value at 5 % significance is 10). Comparing the price coefficients under the respective columns shows that the IV approach corrects the upward endogeneity bias in milk price.

The RCL demand is estimated via simulated GMM procedure that accounts for price endogeneity following the estimation algorithm proposed earlier. We simulate consumer unobservable characteristics Θ in (2) using Halton draws from a standard normal distribution. This procedure minimizes simulation error and reduces the run time for the model substantially (Bhat, 1999; Train, 1999).[8] With only milk fat being observed in my sample, we apply the Box-Cox power transformation to this attribute. Nevertheless, the estimation time does not change with multiple attributes being power transformed, as long as λ is not allowed to vary across the various attributes.

The estimation results show that the logarithmic specification outperforms the rest of possible functional forms, which attests to consumers having diminishing marginal utility of milk fat. This is in contrast to previous studies (for example BLP, 1995; Nevo, 2001; Villas-Boas, 2007; Nakamura and Zerom, 2010; Bonnet et al., 2009; Bonnet and Dubois, 2010) which rely on ad hoc specified linear indirect utility function. Given its empirical superiority, the major analyses are based upon the logarithmic specification of the RCL model.[9]

The results from the RCL demand model are presented in table 4. The majority of the parameter estimates are statistically significant with their signs conforming to theoretical expectations. The results show that consumer heterogeneous taste for milk attributes, such as fat

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[8] For a given λ, it takes the model two hours to run, whereas we use ten λ initial values

[9] Results from other specifications are available upon request

content and price, is mostly accounted for by observed demographics. Price has a large and significant negative impact on the milk purchase of an average consumer (-17.88), which becomes even more so for households with children below 18 years of age (-5.45). However, price does not seem to be as important for households with older heads (3.35), which may have to do their increased need for specialty milk (for example, older people are more likely to develop lactose-intolerance and lactose-free milk becomes a necessity for them). The distribution of consumer valuation of milk price is presented in figure 1a. These measures extend from -57 to 0.78 with a vast majority of consumers deriving disutility from the price and only less than 0.01 % derives utility from it. The value of milk fat diminishes with increasing per capita incomes across households (-0.91), and older household heads (-0.55). In the light of increased health conscience and likely reduction in physical activity, older consumers may prefer lower fat milk. Milk fat distribution is almost symmetric and resembles a normal distribution with mean zero (figure 1b). Given that unobserved demographics do not explain the consumer valuation of milk fat, this speaks to a fact that milk fat is horizontally differentiated. More specifically, milk consumers seem to derive utility from the amount of milk fat that corresponds to their preferences for this attribute, while possible discrepancies yield them disutility.[10] The significant positive point estimates of heterogeneity in the mean utility δ_{jt}, contributed by per capita income (1.95), household head's age (0.27), and number of children below 18 (3.46), imply that relatively richer households with older heads and more children derive higher utility from milk in choice set than from the outside option.

Elasticity estimates from multinomial logit and RCL demand are presented in table 5. Own-price elasticities for the logit model (column 1) vary significantly across the milk

[10] In many cases horizontally differentiated products are priced uniformly, which seems to be the case for milk with different milk fat content

manufacturers (from -3.95 for the milk by manufacturer 3 to as high as -1.13 for the private labels). This supports the conjecture that specialty milk (such as lactose free, organic produced by manufacturers 3 and 4) are viewed as luxury products relative to regular milk. However, elaticity measures from logit demand should not be relied upon in many situations given the unrealistic nature of their substitution patterns (for example, retailer 2 has the lowest (in absolute value) own-price elasticity, which is accounted for by its relatively lower market share). RCL own-price elasticities, unlike logit estimates (-2.47), are not much apart across manufacturers. However, private labels are still the least elastic products, while lactose free milk is the most elastic (-2.84). Interestingly, demand for private label products is the most sensitive to changes in national brand milk prices (0.10), which implies that consumers would rather substitute retail brands of milk for manufacturer brands in case any of the latter sees an increase in price.

Following the two-step procedure, we estimate the demand model once and use the demand estimates to navigate through the supply models considered in this study (Goldberg and Verboven, 2001). This allows for obtaining manufacturer and retailer level market power estimates implied by different supply scenarios, even though manufacturer marginal costs are unobserved. Market power is measured by Lerner Index of price over marginal cost markup. Table 6 reports total vertical Lerner Index and recovered marginal cost estimates across supply interaction scenarios. Lerner Index ranges from the lowest 38 % in the manufacturer level collusion to as high as 77.8 % in a vertical cartel. The markup distribution is rather flat for the manufacturer collusion scenario, and it is even possible to observe negative markups as in Villas-Boas (2007).[11] As for the marginal cost estimates implied by various scenarios, they extend from 10.6 cents per half a pint in manufacturer collusion to 24 cents in retail collusion.

[11] Even if the underlying model is assumed to be true, negative markups can be observed for products that have been loss leaders for milk manufacturers and/or retailers in certain markets

Results from the Rivers and Vuong (2002) non-nested test procedure for the basic and generalized RCL demand models are presented in table 7. More specifically, these are test statistic values obtained from pairwise comparison of incompletely specified models in (18). For a given pair of models, a test statistic value being less than the lower bound of a critical value (-1.64 at 5 % significance level) implies the model under null is correctly specified, while a test statistic exceeding the upper bound (1.64) is supportive of the alternative model. Any value of test statistic between the critical values implies both models are specified correctly. Results from the basic RCL demand model (upper part of table 7) show that at 5 % level of significance the hybrid model outperforms all competing scenarios, while the manufacturer collusion provides the worst fit. Outcomes from a more general RCL demand change the predicition of the testing procedure drastically (lower part of table 7). Namely, a nonlinear pricing model with powerful retailers (3.1) turns out superior to competing scenarios at 5 % level of significance, while manufacturer-level collusion being the most unlikely scenario. The test results are robust to estimation procedure (NLS, GMM) and functional form of the marginal cost (exponential, linear).

The fact that retailers have been reshaping the vertical competitive structure to their advantage is buttressed by findings from previous studies (see for example Villas-Boas, 2007; Bonnet and Dubois, 2010). Moreover, the retail level cross price elasticity estimates in this study (table 5) are rather small, which supports the conjecture that retailers are not engaged in a tough competition (same is true for PL milk). Admittedley, however, supply models considered here do not provide an exhaustive representation of manufacturer and retailer interactions in a vertical context. Neither do most scenarios specify how retail chains might use national brand (NB) and PL milk differently on horizontal and vertical competitive landscapes (for example retailers may use strong PL strategically against manufacturers to negotiate lower invoice prices for NB milk).

Therefore, the finding of manufacturers competing perfectly, while letting retailers claim the vertical markups, may well be the outcome of major retail chains successfully using their store brands.

It is believed that the emergence of PL products empowered major retailers both on the horizontal and vertical competitive landscape (Berge's-Sennou, 2006). Steiner (2004) presents some historic evidence that supports this conjecture. Specifically, while NB prices are defined to an important extent by inter-brand competition, PL prices seem to be rather flexible for the following reasons:

i. Stores in a chain price the PL products uniformly in a given market, which rules out intra-brand competition.

ii. Unlike NB products, PLs are mostly immune to inter-brand competition, simply because retail chains do not carry competing PL brands; moreover, the latter are not directly comparable in many cases. Even if they are comparable for certain products (for example milk), consumers may perceive them as distinct store brands. Search costs and store loyalty further enhance retailer flexibility in pricing PLs.

Thus, reputable store brands put retailers in a position to negotiate lower prices not only for PLs, but also NB products (Morton and Zettelmeyer, 2000). In the result, the percentage markups for PL are higher than those for NB products, even though PL are generally priced lower. Steiner (2004) defines this as a major "regularity" that has prevailed in all markets recently, and the empirical results from this study provide a strong support for this conjecture. Namely, even though PL milk is relatively much cheaper than NB (table 2), markups on retailer markups on PL milk are much higher under any scenario (table 8) as suggested by respective elasticity estimates.

Testing across non-linear pricing models that incorporate finer details as to how participants in a vertical chain interact would help understand the potential sources of market power (as in Bonnet and Dubois, 2010).

Conclusions

Understanding competitive nature in milk markets has gained in importance in the face of rising retail concentration in the U.S. This is exemplified by the USDA and DOJ joint effort to better understand the competitive atmosphere in milk markets, as some of the recent developments in the milk marketing system may have key implications for milk accessibility and availability.

The objective of this manuscript is to contribute to the knowledge of government agencies and other interested parties on the degree of downstream competition in the milk market. Specifically, it studies the market conduct of milk manufacturers and major retail chains in a U.S. Midwestern state. Following the menu approach, we employ a random coefficient logit demand model (RCL) to investigate several supply scenarios ranging from Stackelberg in Bertrand-Nash to vertical cartel. This study contributes to the literature in the following important ways. First and foremost, we generalize the RCL demand model via Box-Cox power transformation. While previous studies rely on ad hoc specified linear indirect utility, this procedure allows data to determine utility functional form. Secondly, identifying power of demand is enhanced by modeling annual variation in consumer demographics along with cross-sectional and time series variation in milk consumption. Furthermore, the choice set for milk is allowed to vary across markets.

The results are most supportive of a supply scenario in which manufacturers pursue their interests as individual enterprises, while retailers operate as a unity. The conjecture of major retail chains becoming relatively powerful vis-à-vis upstream players is supported by findings from similar studies and anecdotal evidence. Moreover, the finding of small retail cross price effects in this study implies little competition among major chains.

Admittedley, however, supply models considered in this study do not provide an exhaustive representation of manufacturer and retailer interactions in a vertical context. Neither do most scenarios specify how retail chains might use national brand (NB) and PL milk differently on horizontal and vertical competitive landscapes. Therefore, the finding of powerful retailers vis-à-vis milk manufacturers may well be the outcome of major retailers successfully using their strategic weapon (PL) against manufacturers. To that end, the PL milk in this study conforms to some "regularities" (Steiner, 2004), which is supportive of PL being an important competitive tool both on the horizontal competitive landscape and vertically.

With the increasing prevalence of the RCL demand model in empirical IO, the supply model selection bias may have a formidable impact on policy implications. Specifically, the empirical results from the generalized RCL demand specification show that major retailers are more powerful than they would appear otherwise. Given the concentration level of this market and the small presence of Wall-Mart, this seems a plausible scenario.

An important limitation of this study is that it relies upon static models of vertical relationships. One way to extend this study is, therefore, incorporating dynamic scenarios, the importance of which increases when strategic considerations are in place, especially in highly concentrated (oligopolistic) markets.[12] Another limitation is that no distinction is allowed in the way the retail chains market PL and NB products (for example, retailers may use major NB milk to attract traffic, while utilizing PL milk strategically against rival chains and manufacturers).

[12] Fundamental reasons may also require dynamic supply models, as firms' own stock may affect their future decisions

Therefore, modeling non-linear pricing scenarios that incorporate finer details, as to how participants in a vertical chain interact, would help shed light on the potential sources of market power.

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Table 1 Descriptive Statistics for Products

Variable	Median	S.D.
Aggregate milk share in IRI city 1 (%)	43.21	4.44
Aggregate milk share in IRI city 2 (%)	37.16	7.92
Container size (pint)	5.00	1.74
Product share across markets (%)	1.47	2.74
Price (cents/half a pint)	22.65	14.73
Aggregate retailer market share across markets (%)		
Retailer 1	11.18	5.43
Retailer 2	5.48	2.79
Retailer 3	52.38	13.59
Retailer 4	14.13	3.22

Source: Own calculations.

Table 2 Products defined and respective prices

IRI-City	*Manufacturer*	*Retailer*	*Fat Content*	*# Markets*	*Price* Median	*Price* S.D.
1	Manufacturer 1	2	Skim	78	14.73	1.76
1	Manufacturer 1	2	Reduced	78	14.92	1.80
1	Manufacturer 1	2	Whole	78	15.08	2.01
1	Manufacturer 2	1	Skim	78	19.91	2.89
1	Manufacturer 2	3	Skim	78	41.15	9.07
1	Manufacturer 2	1	Low	53	39.44	11.94
1	Manufacturer 2	1	Reduced	78	19.32	2.70
1	Manufacturer 2	3	Reduced	78	41.78	9.55
1	Manufacturer 2	1	Whole	78	19.61	1.97
1	Manufacturer 2	3	Whole	78	41.53	9.31
1	Manufacturer 3	1	Skim	78	48.12	2.04
1	Manufacturer 3	3	Skim	78	46.20	3.07
1	Manufacturer 3	1	Low	41	49.25	2.40
1	Manufacturer 3	1	Reduced	78	48.34	2.55
1	Manufacturer 3	3	Reduced	78	46.22	2.90
1	Manufacturer 3	1	Whole	66	47.20	2.62
1	Manufacturer 3	3	Whole	78	45.77	2.74
1	Private Label	1	Skim	71	14.43	1.74
1	Private Label	3	Skim	78	13.54	1.70
1	Private Label	3	Low	78	13.58	1.63
1	Private Label	1	Reduced	71	14.35	1.63
1	Private Label	3	Reduced	78	14.01	1.86
1	Private Label	1	Whole	71	14.57	1.63
1	Private Label	3	Whole	78	13.46	1.81
2	Manufacturer 4	1	Skim	65	45.86	3.40
2	Manufacturer 4	1	Low	63	45.80	4.00
2	Manufacturer 4	1	Reduced	65	45.76	3.55
2	Manufacturer 4	1	Whole	65	45.91	3.42
2	Manufacturer 1	2	Skim	78	16.02	1.84
2	Manufacturer 1	2	Reduced	78	16.65	2.22
2	Manufacturer 1	2	Whole	78	16.83	2.29
2	Manufacturer 2	3	Skim	78	39.64	8.10
2	Manufacturer 2	6	Skim	78	38.94	6.99
2	Manufacturer 2	6	Low	78	40.72	3.28
2	Manufacturer 2	3	Reduced	78	40.38	8.35
2	Manufacturer 2	6	Reduced	78	38.75	7.13
2	Manufacturer 2	3	Whole	78	39.58	9.01
2	Manufacturer 2	6	Whole	78	38.83	7.77

2	Manufacturer 3	3	Skim	78	45.53	2.63
2	Manufacturer 3	6	Skim	78	48.15	4.02
2	Manufacturer 3	3	Low	42	45.92	1.58
2	Manufacturer 3	6	Low	78	47.20	3.01
2	Manufacturer 3	3	Reduced	78	45.55	2.57
2	Manufacturer 3	6	Reduced	78	48.45	4.37
2	Manufacturer 3	3	Whole	78	45.07	2.50
2	Manufacturer 3	6	Whole	63	45.41	3.70
2	Private Label	2	Skim	43	13.12	1.00
2	Private Label	3	Skim	78	13.97	1.39
2	Private Label	6	Skim	78	14.87	1.29
2	Private Label	3	Low	78	13.47	1.40
2	Private Label	6	Low	78	14.63	1.34
2	Private Label	2	Reduced	43	13.15	1.00
2	Private Label	3	Reduced	78	14.12	1.56
2	Private Label	6	Reduced	78	15.00	1.34
2	Private Label	2	Whole	43	13.29	1.00
2	Private Label	3	Whole	78	13.51	1.48
2	Private Label	6	Whole	78	14.78	1.52

Note: There are altogether 57 products defined. Prices are in cents per half a pint of milk. The fifth column represents the number of four-week periods that respective products were offered in the market (i.e., max of 78 in each IRI city).

Table 3 Results from the Multinomial Logit model of demand

	Logit			IV Logit		
Variable	(a)	(b)	(c)	(a)	(b)	(c)
Price	-8.440 *(0.215)*	-8.439 *(0.215)*	-8.758 *(0.205)*	-8.713 *(0.251)*	-8.712 *(0.251)*	-8.998 *(0.242)*
Milkfat		-0.196 *(0.009)*	-1.077 *(0.043)*		-0.191 *(0.010)*	-1.297 *(0.051)*
Mean(Income($US)/Family size)			1.297 *0.086*			1.379 *0.108*
Mean(Household head's age)			0.535 *0.069*			0.857 *0.098*
Mean(Number of children < 18)			1.749 *0.097*			1.820 *0.106*
R^2	0.940	0.940	0.946			
F statistic: Cost coefficients=0					82.167	

Note: The dependent variable in each regression is the difference between the log of actual market shares and that of the outside good. All regressions include product fixed effects.
Source: Own calculations.

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	**-17.886**	0.134	0.198	**3.351**	**-5.451**
	0.441	*0.101*	*0.312*	*0.428*	*0.320*
Constant	-0.159	**0.364**	**1.952**	**0.279**	**3.464**
	0.184	*0.056*	*0.145*	*0.121*	*0.178*
Fat content	-0.006	-0.115	**-0.912**	**-0.556**	**-1.014**
	0.007	*0.566*	*0.438*	*0.259*	*0.451*
GMM objective			752.8		
χ^2 stat			6.25E+04		
Price coef.>0			0.017%		

*GMM estimates are obtained based on 4139 observations. Bold identifies the estimates that are statistically significant at 5 % significance level. Standard errors are in italic. *Estimates are obtained via minimum distance procedure.*

Figure 1.a

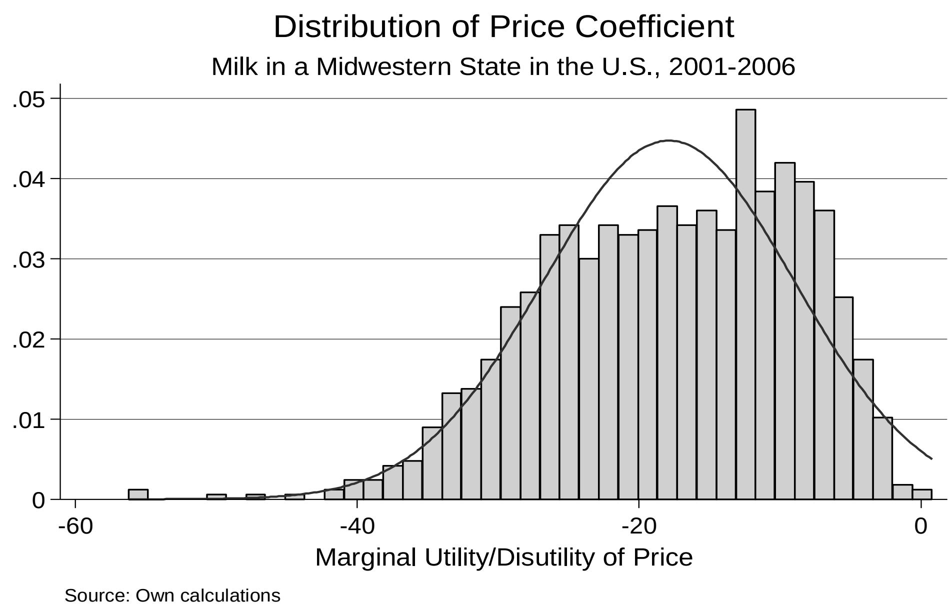

Figure 1.b

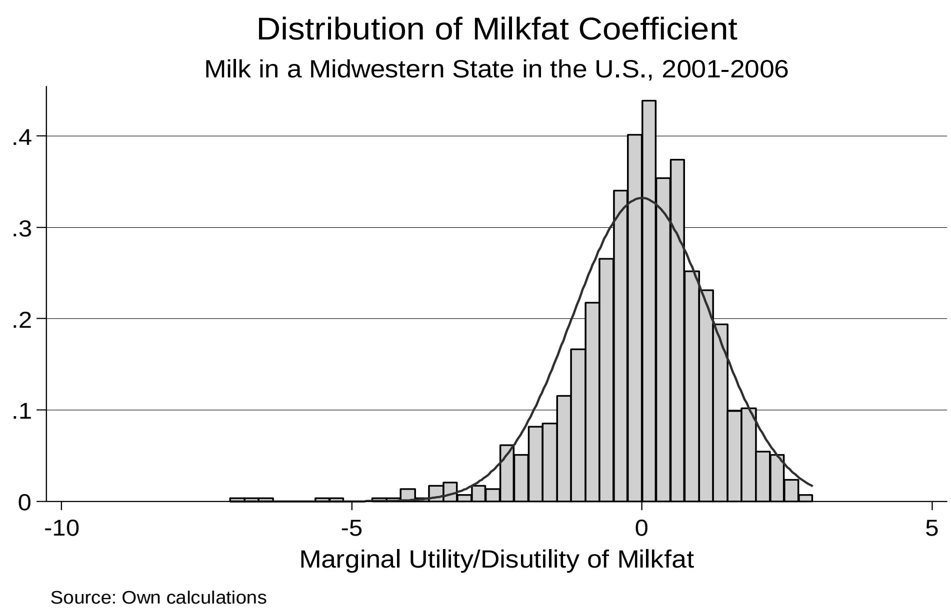

Table 5 Mean elasticity estimates for logit and random coefficient demand models

	Logit Model		RCL Model	
	Own	Cross	Own	Cross
Manufacturer				
1	-1.325	0.017	-2.835	0.002
2	-3.003	0.017	-2.699	0.012
3	-3.951	0.017	-2.652	0.003
Private label	-1.132	0.015	-2.479	0.109
4	-3.868	0.019	-2.848	0.001
Retailer chain				
Chain 1	-2.900	0.018	-2.930	0.022
Chain 2	-1.253	0.017	-2.635	0.002
Chain 3	-2.678	0.016	-2.564	0.068
Chain 4	-2.838	0.016	-2.419	0.033
Average all	-2.545	0.017	-2.641	0.038

Source: Own calculations.

Table 6 Vertical Lerner Index (%) and marginal cost (cents) across the supply scenarios

	Lerner Index		Marginal cost	
Supply scenario	Median	S.D.	Median	S.D.
1. Stackelberg in Bertrand-Nash	57.1	50.3	13.4	12.8
2. Hybrid model (retailers own private labels)	57.6	27.0	12.7	10.1
3.1. Nonlinear pricing w/ retailers as residual claimants	45.5	14.7	12.6	7.0
3.2. Nonlinear pricing w/ manufacturers as residual claimants	41.9	36.4	15.5	5.4
4. Manufacturer level collusion	40.4	78.9	10.6	16.6
5. Retail level collusion	81.2	52.6	24.0	12.7
6. Vertical cartel	80.7	31.9	20.9	7.0

Note: Lerner Indices reported above are computed as $(p-c)/p$ *, where* $(p-c)$ *represents the total of milk manufacturer and retail chain mark-ups.*
Source: Own calculations.

Table 7 Pair-wise non-nested test for supply scenarios

$$R_T = \frac{\sqrt{T}}{\hat{\sigma}_T}\left(\Upsilon_t^1(\hat{\theta}^1) - \Upsilon_t^2(\hat{\theta}^2) \right) \rightarrow N(0,1)$$

Test results from a restrictive demand model

Hypothesis (H_1)	Hypothesis (H_2) 1	2	3.1	3.2	4	5	6
1. Bertrand-Nash in price		1.75	0.08	-1.41	-5.70	-0.28	-0.68
2. Hybrid			-2.30	-4.35	-10.24	-1.95	-3.35
3.1. Nonlinear pricing				-1.52	-5.86	-0.36	-0.78
3.2. Nonlinear pricing					-3.51	0.93	0.60
4. Manufacturer collusion						2.87	2.66
5. Retailer collusion							-0.39

Test results from a more general demand model

Hypothesis (H_1)	Hypothesis (H_2) 1	2	3.1	3.2	4	5	6
1. Bertrand-Nash in price		0.80	1.03	-0.65	-3.23	-0.49	0.12
2. Hybrid			0.26	-1.66	-4.60	-1.47	-0.77
3.1. Nonlinear pricing				-2.00	-5.06	-1.80	-1.08
3.2. Nonlinear pricing					-2.33	0.15	0.71
4. Manufacturer collusion						1.83	2.23
5. Retailer collusion							0.57

Source: Own calculations.

Table 8 Retailer markups for different brand milk under collusive and non-collusive scenarios

	Manuf. 1		Manuf. 2		Manuf. 3		Manuf. 4		Manuf. 5	
	Median	SD	Median	SD	Median	SD	Median	SD	Median	SD
Non-collusive models	35.6	5.0	46.1	9.9	45.2	10.5	56.0	17.6	37.7	5.8
Collusive models	112.0	20.6	73.1	19.5	62.5	13.7	119.8	27.1	59.6	8.7

Source: Own calculations.