Vertical Channel Analysis of the U.S. Milk Market

Abstract

The research in this paper extends the standard random coefficient logit demand (S-RCL) framework using a Box-Cox transformation of the attribute space (BC-RCL) to empirically investigate vertical conduct scenarios in milk manufacturing and retailing. S-RCL relies on ad hoc linear indirect utility that assumes constant marginal utility of attributes. The BC-RCL model relaxes this assumption allowing the data to determine the functional form of utility. Because using product-level data does not allow for an analytical solution for the power transformation parameters, we propose an algorithm to estimate the transformation and consumer heterogeneous taste parameters altogether. The supply selection bias associated with linear indirect utility is shown to have formidable policy implications. Compared to S-RCL, retailers under BC-RCL demand are shown to have more market power using a different best-fitted supply scenario. Elasticity and super-elasticity estimates are presented.

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

JEL Codes: D22, L13

Introduction

Rising concentration in several U.S. retailing sectors (food, hardware, discount etc.) 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 upstream supply sectors (farming, parts manufacturing, etc.) and consumers. When an industry evolves toward greater concentration, it usually means that firms either seek market power that confers higher output prices on their buyers or lower input prices on the procurement side, or the firms actively seek scale or scope economies to gain in efficiency. 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 case, an oligopolistic group of manufacturers may own some of the retail outlets (for example, gasoline markets) with important decisions on vertical interactions and strategic variables being made at manufacturer-level. The vertically integrated manufacturers may have the incentive to charge high prices to their non-integrated rivals in downstream markets to give a strategic edge to their own outlets. (Hastings 2004; Hastings and Gilbert 2005). Villas-Boas (2007) offers further discussion on other possible vertical market outcomes.

One unifying theme emerging from past literature is that abstraction from vertical considerations in empirical studies of retail firm behavior under imperfect completion can lead to biased estimates and inferences that in turn result in erroneous policy recommendations. Therefore, developing models that flexibly consider the pricing impacts from horizontal competition within the manufacturing and retailing sectors along with the potential for imperfect competition in the vertical channel is of great theoretical and empirical value.

The primary objective of the research in this study is to empirically analyze the U.S. milk marketing chain with an emphasis on the relationship between milk manufacturers and retailers. There has been a growing interest in milk markets recently, motivated in part by speculations that retailers may have been exercising market power driven mostly by increasing retail concentration (U.S. Government Accountability Office). During 2010 and as part of multi-dimensional evaluation of competition in agriculture, the USDA and USDOJ organized a dairy workshop in Madison, WI with a goal to provide policymakers an improved understanding of market conditions that determine farm and consumer prices (U.S. Department of Justice, 2011). [1]

Our empirical investigation of structural changes in the milk supply chain is based on analysis of two distinct metropolitan markets in a U.S. Midwestern state. Both markets have a high level of wholesale and retail concentration. Our approach is to develop several benchmark models of imperfect vertical competition that can exploit product-level retail scanner data obtained from Information Resources Incorporated (IRI). [2] These data make it possible to work at the brand level in evaluating horizontal and vertical structural impacts on milk pricing and demand. One of our benchmark models is constructed to consider differentiated vertical pricing strategies between national brand (NB) milk and the growing market for private label (PL) milk (Steiner, 2004). Others consider differing forms of collusion and nonlinear pricing.

[1] The USDOJ along with several state attorney generals challenged Dean Food acquisition of Foremost Farms, USA leading to divestures of the *Golden Guernsey* brand name a large milk bottling plant in south central Wisconsin to preserve competition in Michigan, Illinois and Wisconsin (Janhnke, 2011). Dean Food has also recently settled two 100+ million dollar lawsuits that alleged Dean Food of conspiring to keep farm prices artificially low (D'Ambrosio, 2011, Yahoo, 2011).

[2] Aggregate market share of three major retail chains made up 70 % of the total market share in these markets. In addition, we observe the same chains for the entire study period, which allows for tracking retail behavior.

While a considerable body of research has explored various aspects of the U.S. milk market, only a few consider the full supply channel while also incorporating recent methodological developments in demand analysis. Two leading examples are Lopez and Lopez (2009) and Richards, Allender and Hamilton (2011). In the present paper, we extend the standard random coefficient logit demand (S-RCL) framework (Berry, Levinsohn and Pakes (BLP) 1995; Nevo 2001) using a Box-Cox (Box and Cox 1964) transformation of the attribute space (BC_RCL). S-RCL relies on ad hoc linear indirect utility that assumes constant marginal utility of attributes. The BC-RCL model relaxes this assumption allowing the data to determine the functional form of utility. We follow Villas-Boas (2007) in constructing the menu of vertical market structures.

Most previous studies of supply chains have relied on a conjectural variation approach to explore retail-level competition in a single industry (Bresnahan 1982; Lau 1982), multiple industries (Hyde and Perloff 1998), or the vertical market (Kadiyali, Chintagunta and Vilcassim 2002; Chintagunta, Bonfrer and Song 2002).[3] While this approach provides some guidance on pricing in relation to perfect competition versus monopoly or monopsony, the critique of conjectural variation methods has been harsh both on theoretical and empirical grounds (Corts 1998; Reiss and Wolak 2007). The menu approach sidesteps such methodological concerns.

The rationale for our use of a random utility discrete choice framework lies in its flexibility in handling a potentially large number of differentiated products provided that

[3] An exception is a study by Sudhir (2001), which explores manufacturer behavior in a vertical context allowing for a strategic retailer in the market.

demand is projected on the attribute space.[4] Of these models, the RCL specification is of special importance in empirical applications because it allows for meaningful correlation among the market offerings to each consumer. Modeling somewhat realistic substitution patterns is in turn crucial for estimating the economic effects which underlie the market power estimates.

By offering a more flexible representation of consumer behavior, we anticipate more reliable inferences of retailer and manufacturer market conduct will follow. To evaluate such a claim, we conduct a comparison of the S-RCL versus the BC-RCL demand structures on the measures of market power and on the selection of the best-fitted supply scenario. We find that use of BC-RCL demand leads to a different "best-fitted" supply-side scenario than when the S-RCL demand is operational. We show that retailers appear less powerful when the restrictions associated with the S-RCL model are imposed.

The use of Box-Cox methods in RCL demand estimation is quite limited. Orro, Novales and Benitez (2005) used a similar approach to test across various transportation demand specifications incorporating consumer-level data. In their case, Box-Cox power transformation parameters were obtained analytically. The present study uses product-level data with consumer purchase decisions unobserved by the researcher. Provided that transformation parameters are functions of actual consumer choices, the researcher is left with no guidance as to how to power transform the demand function empirically. Our contribution of the present study is that it proposes a numerical algorithm to estimate the power transformation and consumer heterogeneous taste parameters altogether.

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[4] Quantity demand systems like the Almost Ideal Demand System of Deaton and Muellbauer (1980) are plagued with the curse of dimensionality, given that budget share equations are functions of prices of all the products in the analysis.

The remainder of this article proceeds as follows. The next section presents the basic RCL demand model and the power transformation technique along with several supply scenarios of vertical interaction. Section three presents the details of estimating the BLP 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.

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). Furthermore, 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, Novales and Benitez 2005). Using two-step procedure (Goldberg and Verboven, 2001) we use demand estimates to infer firm behavior by inverting pricing decision for supply scenarios that extend from Stackelberg in Bertrand-Nash to a vertical monopoly. Given the non-nested nature of supply models considered here, a test procedure by Rivers and Vuong (2002) is performed to infer on the vertical competitive atmosphere in milk markets.

Basic Demand Specification

Milk demand is modeled via a discrete choice framework with consumers choosing from (N + 1) alternatives that include N products and an outside option (non-purchase or purchase at outlets in other markets). 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 by:

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

where U_{ijt} is the indirect utility that consumer *i* derives from choice *j* in market $t = 1, 2, \ldots, T$, 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} is known as milk quality and represents unobserved milk attributes (by researcher), ε_{ijt} is milk characteristics unobserved by consumer, and $c_j = \{0,1\}$ denotes milk purchase at value 1, and non-purchase otherwise. For convenience, ε_{ijt} is assumed to have a mean zero *iid* Type I Extreme Value distribution.

Consumer taste heterogeneity is modeled via systematic, as well as random taste variation (Train 2003) as follows:

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

where α and β are the mean structural 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 the latter is assigned a parametric distribution), respectively, Ψ and Λ measure heterogeneity in consumer tastes. The empirical virtue of this setup is that choice set in a market is meaningfully correlated for each consumer; which yields 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 milk unit j yielding highest utility for a given choice set in market t, we obtain individual choice probabilities given by:[5]

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

The predicted demand for milk *j* in market *t* is simply the aggregate of individual probabilities over the distribution of consumer taste heterogeneity:

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

Economic effects are computed via the following formulas based on the estimates of structural demand parameters:

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

Generalizing Demand

While the use of linear indirect utility is standard for RCL demand analysis, it represents an ad hoc restriction that imposes constant marginal utility of product attributes on the system. For our case, validity of the linearity assumption implies that milk choice probabilities are independent of variations in milk fat for any level of milk consumption. This seems restrictive in light of increasing health consciousness in the U.S., where one might expect consumers to derive lower marginal utility as consumption of milk fat increases. Our BC-RCL demand structure relaxes the assumption of constant marginal utility and allows the data to determine the utility functional

[5] The distributional assumption for ε_{ijt} allows for obtaining analytical formula for individual purchase probabilities.

form (Gaudry and Willis 1978). The finding of a nonlinear indirect utility is tantamount to consumers having diminishing marginal utility of milk attributes. The Box-Cox power transformation can be applied to some or all product characteristics that accept strictly positive values (Box and Cox 1964; Train 2003). Utility is specified as:

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

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

where $\lambda_{jt} = 0,1$ imply a logarithmic and linear indirect utility, respectively.

Supply Scenarios for Vertical Interactions

Six supply scenarios are evaluated. While not exhaustive, they represent a fairly broad scope of vertical interactions between manufacturers and retailers.

1. *Stackelberg in Bertrand-Nash (double marginalization)*

This is a simple Bertrand-Nash pricing framework in both sectors and with manufacturers (retailers) taking the Stackelberg leadership (follower) position in vertical pricing. Equilibrium prices are obtained via backward induction first solving for optimal retail behavior. Retailer *e* in market *t* is characterized by the following profit function:

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

where I_{et} represents 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 marketing *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 are obtained by differentiating (8) with respect to respective retail-level prices as follows:

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

where n_e is the number of active retailers in market *t*. Stacking together optimality conditions for all products in I_{et}, we obtain the price premium over marginal cost markups (ω_t) for retailer *e* in market *t*.

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

where O_e is the retailer *e*'s ownership matrix (equals 1 if both products for an entry are carried by retailer *e* and 0 otherwise), 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.

Manufacturer markups (τ_t) are obtained taking retail optimal behavior as given:

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

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 represents its ownership structure, and $\Delta_{wt}(p(w))$ its response to variations in retail prices:

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

Sensitivity of manufacturer prices to changes in retail prices, represented by $\partial p_{kt}\big/\partial p_{kt}^{w}$, is generally unknown in practical applications, given the fact that manufacturer/wholesale 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, $k=1,...,n$ and a wholesale price p_m^w allowing variation dp_m^w:

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

Applying the above procedure to each optimality condition in (9) and stacking together their respective relationships as in (13), we obtain $G\,dp\text{-}H_m\,dp_m^w=0$, 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 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. Hybrid model

The emergence of successful PLs has the potential to provide retailers with an added dimension of market power in both the horizontal and vertical competitive landscape (Berge's-Sennou, 2006; Morton and Zettelmeyer, 2000). Steiner (2004) presents historic evidence supporting such hypotheses. Large food retailers have the ability to extend the PL footprint over the entire chain and covering hundreds of food items. 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.

The hybrid model stands between Stackelberg Bertrand-Nash model described above and the nonlinear pricing models discussed next. The hybrid model presumes that retailers control private label purchases and eliminate manufacturer markups. This may yield them a competitive edge over NB milk. Retail markups, therefore, remain unchanged (10), while manufacturer markups are expectedly lower than in (11):

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

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

In this 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.

3. Nonlinear pricing models

Two alternative nonlinear pricing models considered allow for manufacturers to obtain marginal cost pricing while retailers claim all profit and vice versa. Though not explicitly modeled, it is presumed that in the presence of bilateral power, some fixed payment is obtained in response to either buying or selling at marginal cost. The explicit modeling of nonlinear pricing scenarios, such as retail slotting fees paid by manufacturers, is limited by data considerations or requires strong assumptions to identify the model (Bonnet and Dubois 2010).

With manufacturers selling at marginal costs (zero markups) retail markups are:

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

In another extreme, retailers follow marginal cost pricing, while manufacturers claim the vertical profit given by:

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

Investigating profit redistribution mechanisms between manufacturers and retailers engaged in a nonlinear pricing contractual relationship is an interesting area of study, however we do not pursue it here (see for example Bonnet and Dubois (2010)).

4. *Collusion at Manufacturer Level*

In this setup, manufacturers maximize their joint profit, with retailers follow a tacit collusive strategy and receive the same markup as in (10). Manufacturers' markups is given by (11), with the only difference being in that manufacturer ownership structure is represented by an identity matrix.

5. *Collusion at Retail Level*

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

6. *Vertical Collusion*

In this extreme scenario manufacturers and retailers act as one vertically aligned enterprise to claim monopoly rents represented by:

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

Procedure for Testing Market Level of Competitiveness

We employ a non-nested testing procedure to infer on the nature of competition in the milk supply chain. We first estimate manufacturer (ω_{jt}) and retailer (τ_{jt}) markups for the supply scenarios considered, which are used to obtain implied vertical marginal costs as follows:

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

The supply model is based upon pair-wise comparisons of respective marginal cost functions:

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

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

The non-nested test procedure by Rivers and Vuong (2002) is used for model selection. 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) within GMM framework). The test statistic measures the distance between the lack-of-fit criteria from the competing stochastic marginal cost functions estimated via NLS or GMM, based on an identifying assumption that observed ($c_{i1t}, ..., c_{i\psi t}$) and unobserved cost shocks (ι_{it}) are orthogonal. (Rivers and Vuong 2002; Bonnet and Dubois 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 underlying in the estimation of competing marginal cost functions and are evaluated at the optimal values of cost parameters from the respective models (i.e., $\hat{\theta}_3^A, \hat{\theta}_3^B$), $\hat{\sigma}_T$ is a consistent estimator of limiting variance of difference between lack-of-fit criteria, the latter being normalized by $\sqrt{T}$.

Under regularity conditions, Rivers and Vuong (2002) show that R_T has a standard normal distribution. A 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 maintains that model under A outperforms B (resp. B outperforms A) and is provided below:

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

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).

Estimation Details for the Generalized RCL model

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 represents 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 (BLP 1995).

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

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

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

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

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

Price endogeneity is yet another issue. It stems from simultaneous determination of milk supply and demand in a structural setting. In addition, certain important determinants of milk demand, such as advertising, specialty milk attributes (organic, lactose-free) are unobserved, which causes omitted variable bias. Lastly, unit prices of milk are imputed via 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 researcher, denoted by $\Delta\xi_{jt}$) are still likely to be correlated with milk prices (Nevo 2001). Therefore, we follow instrumental variable approach to account for milk price endogeneity. Specifically, we use product fixed effects interacted with manufacturer and retailer cost components (Villas-Boas 2007).

The addition of Box-Cox parameters to the model adds another level of difficulty to the estimation procedure. This is the first study to propose a numerical algorithm to obtain λ estimates in the generalized RCL demand (6). More specifically, we add another loop of grid search to the original BLP algorithm to obtain the estimates of Box-Cox (λ) and consumer heterogeneous taste parameters (θ_1, θ_2) in a series of sequential optimization. The detailed steps for running the algorithm are provided below:

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

ii. Use each initial value for 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 BLP algorithm).

iii. Repeat i-ii for all initial values of λ. One way to go about it is conducting 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 when we use Halton draws from the standard normal distribution (Bhat 1999). We present more details on this aspect of the algorithm in the empirical results section.

Data

Data used in this study come from several sources. Weekly fluid milk sales, average price, and milk characteristics are provided by the Information Resources Incorporated (IRI). These cover market-level milk sales at four large supermarket chains in two IRI city-markets in a U.S. Midwestern state from 2001 to 2006. These markets have been rather concentrated in the period of analysis. Three major retailers accounted for around 70 percent of the total market share two of which operate in both markets: retailer #1 and #3. Retailer #3 is the dominant player in both IRI city-markets with an average of about 35 percent of the total food-at-home market share (Market Scope, 2001-06). Since the IRI data is specific to primarily supermarkets, retailers #3 has market share of over 52 % in the sample (table 1). The remaining retailers have relatively lower IRI market shares (over 14 %, 11 %, and 0.5 % 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 city. The market shares of the outside option in the sample (milk sales occurred outside of IRI market) seem realistic in this light and compare well to those from similar studies (over 56 and 62% in the respective cities). Another issue is that specialty milk characteristics (organic, lactose free) are missing for a considerable number of observations, so we do not consider these attributes in this study. We use the content of milk fat as a major form of intrinsic product differentiation. This milk attribute should be an important determinant of milk consumption because of its general association with health and caloric intake, most stores organize milk in the dairy case by fat content and many consumers make a conscious repeated purchase decision based on their taste preferences for a specific milk fat content.

Products are defined as unique combinations of milk manufacturer-retailer chain-milk fat content; which results in 57 products in the two geographic markets (table A1 in reviewer appendix). Prices and quantities of milk sold are obtained by aggregating from weekly to four-week periods. We deflate prices from 2002 onwards using an aggregate CPI measure for urban areas. Private label milk is usually the least expensive option in the choice set, while mostly lactose free milk provided by manufacturer 3 and organic milk by manufacturer 4 are relatively more expensive substitutes. To obtain the actual market shares of milk we define the market size as a product of U.S. per capita milk consumption and the size of populations in respective cities in 2001-06. Market shares 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 Coop Class I milk price. The latter is price that dairy cooperatives receive for their fluid milk from the regulated processors in a particular area and comprise more than 70 percent of the delivered cost of bottled milk (Gould 2006). As for retailer cost components, we use the retail-level electricity prices (EIA), Federal funds effective interest rates (BLS), and retailer total sales (IRI).[6]

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

Finally, samples of demographics from the joint distribution of consumer characteristics were taken from the Current Population Survey for each IRI city (U.S. Bureau of Labor 2001-06). We allow for annual demographic variation for the identification purpose. Overall 1200 consumers from different households were sampled from the whole market. The consumer demographics include total household income, age of the household head, and the number of children less than 18 years of age.

Empirical Results

As an initial exercise, we presume the possibility of price endogeneity and developed a set of instruments from the manufacturer and retailer cost components discussed earlier. To evaluate the instruments, we calculated a Hauseman test statistic from an instrumental variable (IV) logit demand model and standard logit model with exogenous regressors (see table 2). The test results easily reject the null of invalid instruments leading us to account for price endogeneity in subsequent work. A simple comparison of price coefficients under the respective columns in table 3 reveals that the IV approach corrects an otherwise upward endogeneity bias in the coefficients of milk price.

The BC-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 substantially reduces the run time for the model (Bhat 1999; Train 1999).[7] With only milk fat observed in the data, we apply the Box-Cox power transformation to this attribute. The estimation results show that the logarithmic specification ($\lambda=0$) outperforms the rest of functional forms considered, which attests to consumers having

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

diminishing marginal utility of milk fat. Given its empirical superiority, we base much of our further analysis upon the BC-RCL model.[8] For comparison purposes, we also estimate the S-RCL demand under the various supply channel scenarios and report the findings.

Table 3 contains the regression results of the BC-RCL demand model without supply channel considerations. Most parameter estimates are statistically significant and consistent with theory. The results show that consumer taste for fat content and price is mostly accounted for by observed demographics. Price has a large and significant negative impact on the milk purchase for an average consumer (-17.88), which intensifies 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 with ingrained purchasing patterns that might be related to health or decreased share of milk in food budgets. The value of milk fat diminishes with increasing per capita income (-0.91), and the age of household head (-0.55). In the light of increased health conscience and likely reduction in physical activity, this may be reflective of older consumers switching to lower fat milk. Contributions of per capita income (1.95), household head's age (0.27), and number of children below 18 (3.46) to the mean utility provide evidence that relatively wealthier households with older heads and more children prefer milk purchase from sampled stores to the outside option.

The distribution of consumer valuation of milk price and milk fat are presented figure 1. For price (top panel in figure 1), consumer valuation measures range from -57 to 0.78 with a vast majority of consumers deriving disutility from the price and only less than 0.01 % enjoying higher prices. Milk fat distribution is almost symmetric and resembles a mean zero normal distribution (lower panel in figure 1). Given that unobserved demographics do not explain the

[8] Results from other specifications are available upon request

consumer valuation of milk fat, this may speak to the fact that milk fat is a horizontally differentiated attribute. Put simply, not all consumers enjoy milk fat.[9]

Elasticity estimates from multinomial logit and the BC-RCL demand are compared in table 4. Own-price elasticities for the logit model (column 1) vary significantly across the milk manufacturers (from -3.95 for the milk by manufacturer 3 to as high as -1.13 for the private labels) and reflect consumers being more sensitive to higher priced specialty milk prices (lactose-free, organic) than those of conventional milk. However, elasticity 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 highest own-price elasticity, mostly driven by its low market share). The BC-RCL own-price elasticities, unlike logit estimates, are much more stable across manufacturers. However, private labels are still the least elastic products (-2.47), while mostly lactose free milk by manufacturer #1 is the most elastic (-2.84). While we report low mean cross-price elasticities for all products, consumers are relatively far more responsive to purchasing private labels in response to NB price changes compared to any other brand.

Following the two-step procedure, we estimate the demand model first 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 specific market power estimates for each supply scenario. Market power is measured by the Lerner Index of the markup from inferred marginal cost over the observed price. Table 5 reports the total vertical Lerner Index and recovered marginal cost estimates for each model in the menu. Lerner Indices range

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

from the lowest (40.4 %) for manufacturer level collusion to as high as (80.7 %) for vertical cartel. The markup distribution is rather flat for the manufacturer collusion scenario; in addition we obtain negative markups for some products in certain periods (see Villas-Boas (2007) for more on this).[10] Average vertical marginal cost estimates implied by various scenarios extend from 10.6 cents per pint in manufacturer collusion to 24 cents in retail collusion.

Results from the Rivers and Vuong (2002) non-nested test procedure are presented in table 6. Specifically, these are test statistic values obtained from pairwise comparison of incompletely specified models given by (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 correctly specified. Results from the S-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 the BC-RCL demand change the prediction of the testing procedure drastically (lower part of table 7). Namely, a nonlinear pricing model with powerful retailers (3.1) turns out be the superior choice relative to the other competing scenarios. Both the standard and Box-Cox versions of RCL demand show that manufacturer collusion is the most unlikely scenario. The test results are robust to estimation procedure (NLS, GMM) and functional form of the marginal cost (exponential, linear).

Using our elasticity estimates and milk prices we calculate the super-elasticities for demand model #3.1. Super-elasticities evaluates the curvature of consumer demand by

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

meausring the percentage change in own-price elasticity for a percent increase in prices (Willis and Klenow 2006). Super-elasticities can shed light on understanding firm motivation to alter own prices in response to cost shocks. Figure 2 presents “super-elasticity” estimates across products in each market which range from 0.004 % to 0.042 %. Interestingly, the estimates for PL milk are rather low in value vis-à-vis NB milk, with the latter demonstrating more volaitility across markets. Thus, it appears that NB milk becomes increasingly price sensitive in response to higher prices but less price sensitive when prices decline. Such a condition suggests that retailers can identify a pricing postion, possibly in relation to PL, in which there is a low incentive to increase or reduce NB prices.

Our findings suggest that retailers have used market power to reshape the vertical competitive structure to their advantage. This is buttressed by findings from other 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 small, which supports the conjecture that retailers are not engaged in a cross-brand competition (same is true for PL milk). Admittedly, 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 NB and PL milk differently on horizontal and vertical competitive landscapes (for example retailers may use powerful PLs strategically against manufacturers to negotiate lower invoice prices for NB milk). Therefore, our finding that retailers claim the vertical markup and manufacturers price competitively may well be the outcome of major retail chains successfully using their PLs as a way to leverage price bargaining in the vertical chain.

Conclusions

Understanding the competitive landscape in U.S. food markets is an important research question in the face of rising retail concentration. The objective of the research in this manuscript is to develop useful models that can test for imperfect competition between food retailers and manufacturers and to evaluate vertical channel pricing for U.S. milk markets. This study provides information about milk markets in ways that are consistent with recently litigated antitrust cases involving milk manufacturers and with recent joint inquiries about competition in agriculture by the USDOJ and USDA. We study the market conduct of milk manufacturers and major retail chains in two markets in a U.S. Midwestern state. Consumer demand is modeled with a RCL framework with Box-Cox transformations of the attribute space. Following a menu approach, we investigate several vertical supply scenarios that include nonlinear pricing models, a model with differentiated pricing between NB and PL, and models of vertical collusion.

This study contributes to the literature in several ways. First, previous studies using the RCL demand rely on ad hoc linear indirect utility that conforms to a maintained hypothesis of constant marginal utility in the attribute space. Our proposed Box-Cox algorithm allows product-level data to determine utility functional form. Our algorithm chooses a logarithmic transformation of the attribute space thereby rejecting constant marginal utility in milk fat content. If constant marginal utility in the attribute space is a restriction that does not hold very often, then the BC-RCL algorithm may prove useful over a broad range of applications.

We tested each vertical supply scenario using both the S-RCL and BC-RCL demand frameworks. One key finding is that under S-RCL, vertical supply model #2 (hybrid) is the best-fitted one. Under BC-RCL, model 3.1 (first nonlinear pricing) fits best. Therefore, a key finding from our study is that the vertical supply selection bias associated with imposing linear indirect utility in consumer demand is shown to have formidable policy implications about how markets function. While the hybrid model implies retail market power, it also implies that PL pricing power does not translate to a uniform pricing structure for retailers. Under BC-RCL, retailers capture all of the economic rent in the vertical channel for both PL and NB milk.

Lower in absolute value price elasticities for PL milk combined with a tight range of superelasticities suggest that retailers have greater ability to extract rent from consumers using PL products compared to NB products. This finding suggests that PL milk has a differentiated role in the strategic pricing of U.S. milk markets on the demand side. To offer a more refined evaluation of what is happening on the supply side, we need wholesale transaction prices between large manufacturers and retailers along with information about about any other charges or incentives (slotting fees, quantity minumum contracts, volume discounts, manufacture promotions, etc) that could help define the way nonlinear pricing functions.

An important limitation of this study is our use of a static demand model. While milk is neither durable nor storable for long periods, dynamics may be present in milk demand through intertemporally related utilities across the consumption periods. Testing across non-linear pricing models that incorporate finer details as to how participants in the vertical chain interact would help understand the potential sources of market power (see for example, Bonnet and Dubois 2010). These are good topics for future research.

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Table 1. Descriptive statistics

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	0.55	0.27
Retailer 3	52.38	13.59
Retailer 4	14.13	3.22

Table 2. Comparison of results: Logit versus IV Logit-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	

Table 3. Results from the BC- RCL Demand Model

Variable	Means B	Unobserved Demographics σ	HH Income/Family size	HH head's Age	# of Child <18
Price	**-17.886** *0.441*	0.134 *0.101*	0.198 *0.312*	**3.351** *0.428*	**-5.451** *0.320*
Constant	-0.159 *0.184*	**0.364** *0.056*	**1.952** *0.145*	**0.279** *0.121*	**3.464** *0.178*
Fat content	-0.006 *0.007*	-0.115 *0.566*	**-0.912** *0.438*	**-0.556** *0.259*	**-1.014** *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.

Table 4. Mean price elasticity estimates

	IV Logit Model		BC-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

Table 5. Vertical Lerner Indices and marginal cost estimates

	Lerner Index* (%)		Marginal Cost (cents)	
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

*The Lerner Indices and marginal costs represent the total of milk manufacturer and retail chain mark-ups and marginal costs, respectively.

Table 6. Pair-wise non-nested tests between 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_2)

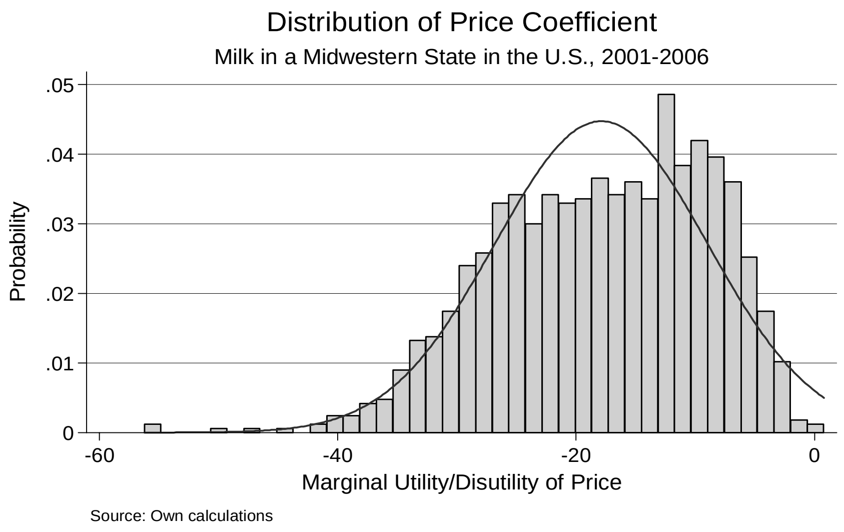
Hypothesis (H_1)	1	2	3.1	3.2	4	5	6
1. Bertrand-Nash in price		1.75	0.08	-1.41	-5.70	-0.28	-0.68
2. Hybrid			-2.30	-4.35	-10.24	-1.95	-3.35
3.1. Nonlinear pricing				-1.52	-5.86	-0.36	-0.78
3.2. Nonlinear pricing					-3.51	0.93	0.60
4. Manufacturer collusion						2.87	2.66
5. Retailer collusion						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

Test results from a more general demand model

Hypothesis (H_2)

Hypothesis (H_1)	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

Figure 1: Empirical distributions of coefficient values



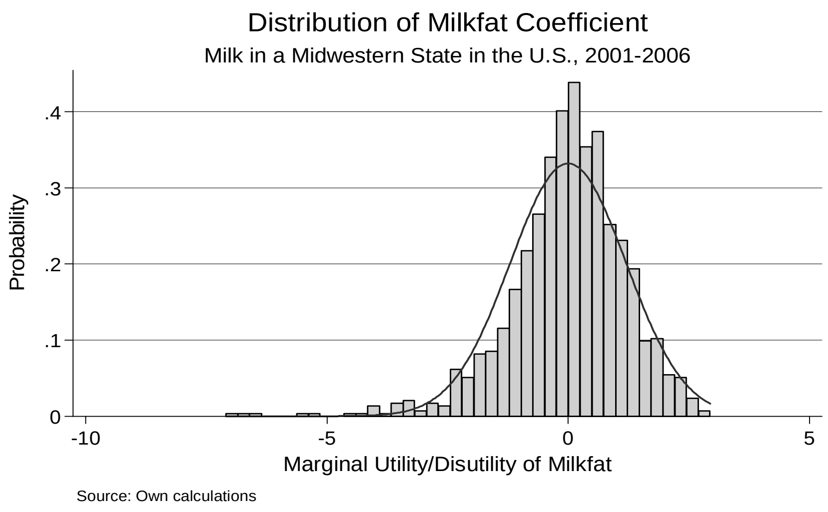
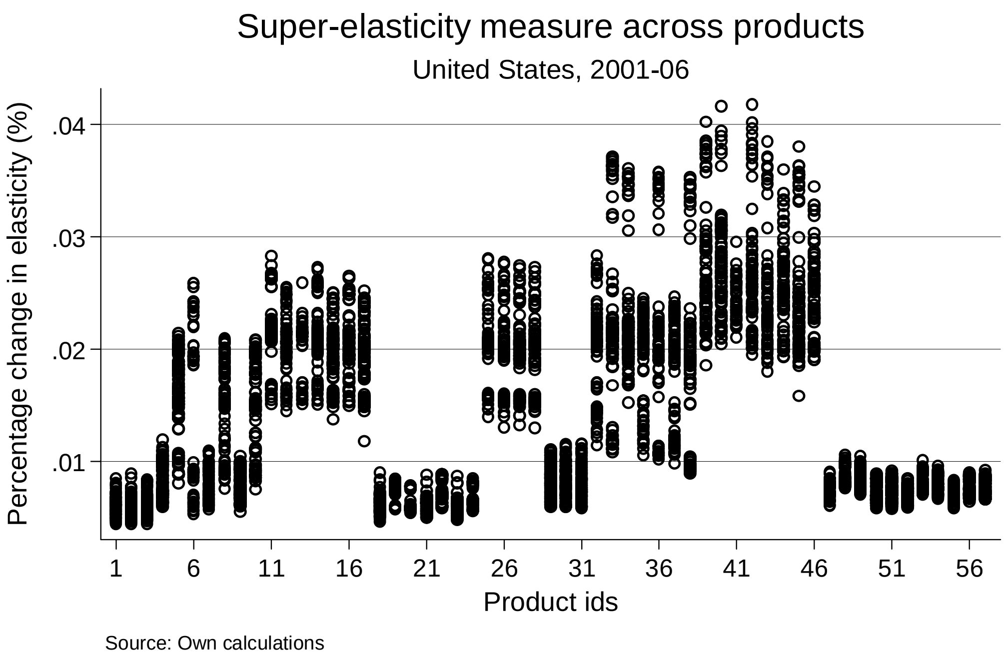


Figure 2. Super-elasticity measure across products



Note: Super-elasticities for milk by a local processor appears in rectangles, private labels are encircled by ellipses

Supprimé:

Reviewer Appendix

Table A1. Products defined and respective prices

IRI-City	*Manufacturer*	*Retailer*	*Fat Content*	*# Markets*	*Price* Median	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	4	Skim	78	38.94	6.99
2	Manufacturer 2	4	Low	78	40.72	3.28
2	Manufacturer 2	3	Reduced	78	40.38	8.35
2	Manufacturer 2	4	Reduced	78	38.75	7.13

2	Manufacturer 2	3	Whole	78	39.58	9.01
2	Manufacturer 2	4	Whole	78	38.83	7.77
2	Manufacturer 3	3	Skim	78	45.53	2.63
2	Manufacturer 3	4	Skim	78	48.15	4.02
2	Manufacturer 3	3	Low	42	45.92	1.58
2	Manufacturer 3	4	Low	78	47.20	3.01
2	Manufacturer 3	3	Reduced	78	45.55	2.57
2	Manufacturer 3	4	Reduced	78	48.45	4.37
2	Manufacturer 3	3	Whole	78	45.07	2.50
2	Manufacturer 3	4	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	4	Skim	78	14.87	1.29
2	Private Label	3	Low	78	13.47	1.40
2	Private Label	4	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	4	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	4	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).